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FOREST/NON FOREST MAPPING USING LANDSAT THEMATIC MAPPER IMAGERY AND ARTIFICIAL NEURAL NETWORKS (ANNs)

A. Stefanidou, E. Dragozi, M. Tompoulidou, I. Z. Gitas
Aristotle University of Thessaloniki,
P.O. Box 248, 54124, Thessaloniki, Greece
E-mail: alexands@for.auth.gr

Forest area and the landscape level spatial pattern of forests are two of the indicators for sustainable forest management in Europe (MCPFE 2003). As they are important for forest policymaking (MCPFE 2007), there is a constant need of timely and accurate information about their current status. The aim of this study was to examine the potential of Artificial Neural Networks (ANNs) in differentiating forest from non-forested areas and to explore how the use of higher-order features, derived from a Landsat-5 TM image, could improve the performance of the ANNs classifier. The features were generated through the application of the Tasseled Cap transformation and Principal Component Analysis (PCA). The study area is a typical Mediterranean region located in the north-east part of Greece. The results from the classification accuracies of the study revealed that the most accurate map (Overall Accuracy (OA) =91,76 %-Kappa Index of Agreement (KIA) =0,787) was generated through the implementation of ANNs on the three bands produced by the application of Tasseled Cap transformation on the Landsat TM image. The comparison of the produced map products with the Pan-European Forest Map 2000 of the Joint Research Centre (JRC) (FMAP 2000), showed that the overall accuracy of the JRC map (OA=78,02 %-KIA=0,446) is lower than the ones of the maps that were produced by ANNs. Finally, it is concluded that, for this study area, the implemented methodology for differentiating areas covered by forest from other classes led to the production of maps of high accuracy, which exceed the adequate accuracy of the FMAP 2000.

Key words: *forest/non-forest mapping; Artificial Neural Networks; Tasseled Cap transformation; Principal Component Analysis.*

Introduction. Interest in the world's forests has grown to unprecedented heights, not only due to the growing awareness of their role in the global carbon cycle but also due to the fact that forests represent some of the most diverse ecosystems on Earth [1, 2]. Forests' degradation can intensify the phenomenon of climate change [3], as well as provoke phenomena, such as desertification [4]. As a result, national governments are looking for ways to strengthen their forest management policies, in order to preserve sustainability in forest ecosystems [5].

As far as the Mediterranean basin is concerned, forests represent a significant part of the flora [6], while they are considered one of the most important ecosystems of the specific geographic area. Nevertheless, nowadays, the Mediterranean forests are vulnerable to various threats, such as forest fires, excessive exploitation, deforestation and degradation [4]. In order for these severe challenges to be confronted, Mediterranean forests require protection and rational management.

The effectiveness of forest management is highly dependent on the availability of accurate and current information regarding the status of the managed areas. Two of the most basic information required by policy and decision makers is the forest cover and how it changes over time [5]. Therefore, there is a constant need for the production of up-to date forest cover maps.

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Satellite remote sensing in combination with Geographic Information Systems constitute an inexpensive and practical solution for the production of land cover maps, as well as for geographic information management [7–9]. Satellite remote sensing, in particular, has been proved as a useful tool in various environmental applications, which, in most cases, require constant monitoring and mapping extensive and inaccessible areas [10].

The satellite data that are frequently used in the field of forest mapping are data from medium (Landsat TM) and coarse resolution sensors, such as MODIS (250 m), AVHRR (1 km) and SPOT-VGT (1 km) [11–15].

Respectively, the classification techniques that have been used, up until now, for forest/non forest mapping include Maximum Likelihood classifier, Artificial Neural Networks (ANNs) [16] and Decision Trees [17]. Examples of ANNs in forest mapping can be found in the international literature [16, 18–23].

ANNs are Artificial Systems that resolve problems inspired by the function of the human brain. Over the past decades, ANNs have been proved to be a widely acceptable tool for environmental applications and, more specifically, in the field of satellite remote sensing [24, 25]. As Atkinson and Tatnall [26] mention that the proven usefulness of ANNs in remote sensing is due to the following advantages:

- ANNs are more accurate and more rapid than the statistical classifiers;
- they have the ability to combine a priori knowledge and realistic physical constraints into the analysis;
- they can be applied on different types of data, facilitating synergistic studies.

In the present study, ANNs were applied considering the advantages presented above, as well as the fact that this artificial technique has not been fully explored for mapping Greek forests.

In spite of the specific classification technique, which, according to the international literature, can significantly increase the mapping accuracy, the overall accuracy can also be improved with the use of additional useful information (e.g. altitude, slope etc.) [27]. However, recent studies have addressed the use of higher-order features, which derive from a variety of spectral transformations of satellite imagery. The spectral transformations analyze the reflectance values of every pixel of the image, producing new values in a different spectral space. The most widely applied spectral transformations include the Kauth-Thomas (Tasseled Cap) transformation [28, 29] and Principal Component Analysis (PCA) [30, 31].

According to the literature, the use of additional features in a classification does not always contribute to the improvement of the map product accuracy. Moreover, the use of numerous additional features may render the classification process time-consuming or even impossible to perform [32]. In this case, it is recommended to decrease the number of features, in order the classification results to be improved [33].

In the present study, higher-order features, which derived from the two above-mentioned image transformations (Tasseled Cap and PCA), were used in combination with ANNs.

The aim of the present study was the investigation of the potential of using Landsat data and ANNs for forest/non forest mapping. The specific objectives were:

- to investigate the potential of using ANNs in forest/non forest classification of a Landsat-5TM image;
- to investigate the potential of applying ANNs for forest/non forest mapping using two images, each of which includes the features derived from the Tasseled Cap and PCA image transformation respectively;
- to investigate the potential of applying ANNs for forest/non forest mapping using an image, which includes the initial bands of Landsat-5TM image and the features derived from the Tasseled Cap image transformation;
- to compare the produced forest/non forest maps with the FMAP 2000.

Study Area and Dataset Description. The study area is the Island of Lesvos, which is located in the Mediterranean region and more specifically in the north-east part of Greece. The Island of Lesvos is characterized by rich flora and is one of the most forested islands of the Aegean Sea. A large percentage of the area of Lesvos is covered by pines, oaks, olive plantations and chestnut trees. Mediterranean-type climatic conditions with hot summers and mild winters, are characteristically prevailing.

Fig. 1. Study area located in Greece

Datasets used in the course of this study, include:

- a Landsat-5TM image acquired over the study area, in May 2002;
- the FMAP 2000, which was used in both the training phase of the classification process and the comparison of the produced maps to this already available pan-European product;
- two independent sets of training and validation points, originating from photointerpretation of very high resolution imagery (Greek National Digital Orthophoto Database, Google Earth);
- additional auxiliary data such as the Land Parcel Identification System (LPIS) data for Greece and the administrative boundaries of Greece.

Dataset Preprocessing. The dataset preprocessing was accomplished in two phases. The first phase included the preprocessing of the data and the transformations of the Landsat-5TM image. The second phase included the collection and photointerpretation of training samples, which were used for the training of the classifier.

Dataset preprocessing and feature extraction. First of all, the preprocessing of the Landsat-5TM image was performed, according to the steps presented in the following flowchart (Fig. 2).

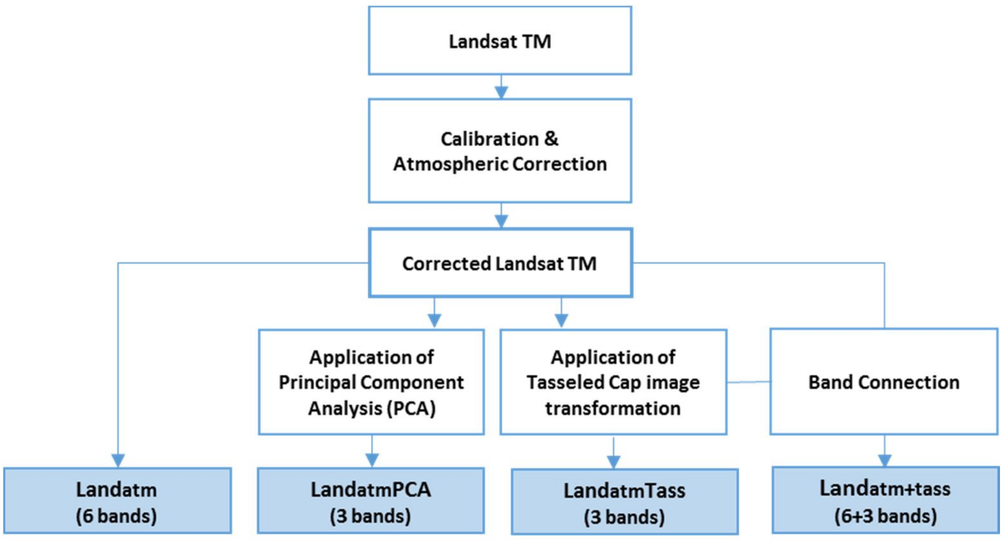

Fig. 2. Landsat-5TM preprocessing flowchart

The first step of the Landsat-5TM preprocessing involved the calibration proposed by Chander and Markham [34], and the «dark-object subtraction» atmospheric correction method [35]. This type of correction aimed, mainly, at the quality improvement of the satellite image.

In order to investigate the specific objectives of the present study, three new images were produced through the implementation of the Tasseled Cap transformation and the Principal Component Analysis (PCA).

More specifically, at first, the Tasseled Cap transformation was applied on the initial Landsat-5TM image. According to the literature, the values of the three new bands derived from this transformation correspond to the overall brightness of the image, the presence of chlorophyll (greenness) and the soil moisture (wetness) [28, 29].

The implementation of the PCA followed. PCA transformation is a linear transformation, which performs image data compression, producing two or three transformed principal components, which tend to be encoded more easily than the initial data [30, 36]. As a result, three new band images were produced.

After completing the above-mentioned tasks, the data produced are the following:

- an atmospherically corrected Landsat-5TM image (Landatm);
- an image (LandatmPCA) which includes the three bands derived from the implementation of PCA on the Landatm;
- an image (LandatmTass) which includes the three bands (brightness, greenness, wetness) derived from the implementation of the Tasseled Cap transformation on the Landatm;
- an image (Landatm+tass) which includes the nine bands derived from the connection of the six bands of the initial Landsat image with the three bands (brightness, greenness, wetness) derived from the implementation of the Tasseled Cap transformation on the Landatm.

Finally, the Island of Lesvos was extracted from all the produced images. The same procedure was performed to the FMAP 2000, in order to be able to compare it with the forest/non forest maps produced in the present study. In addition, the agricultural areas were removed from the study area due to their significant spectral similarity to the forested areas and, consequently, the difficulty of their differentiation [37].

Training samples generation. The generation of the training samples was based on the stratified random sampling method applied on the FMAP 2000.

The number of points was indicated by Fitzpatrick-Lins (1981) Eq.1.

$$N = \frac{Z^2(p)(q)}{E^2}, \qquad (1)$$

for Z=2, p= 85 % and E= 5 %, where p is the expected percent accuracy, q = 100 – p, E is the allowable error, and Z = 2.

The number of points computed by Equation 1, with expected percent accuracy 85 % and allowable error 5 %, was 203. However, in order to avoid spatial autocorrelation [38], the number of the training samples was reduced to 111.

The samples were identified as 'Forest' and 'Non Forest', using the JRC forest definition* and photointerpretation based on the Greek National Digital Orthophoto Database and Google Earth. Samples' identification was made within a radius of 75 meters since the characterization of each point depends on the percentage of forest cover inside this area.

Methodology. After preprocessing the data, the application of the methodology was performed. The steps followed in order to accomplish the specific task is presented in the flowchart below (Fig.3).

* The areas defined as 'forest' are larger than 0,5 ha. These areas are occupied by forest and woodlands with a vegetation pattern composed of native or exotic coniferous and/or broadleaved trees. The forest trees are taller than 5 m in height with more than 30 % crown cover.

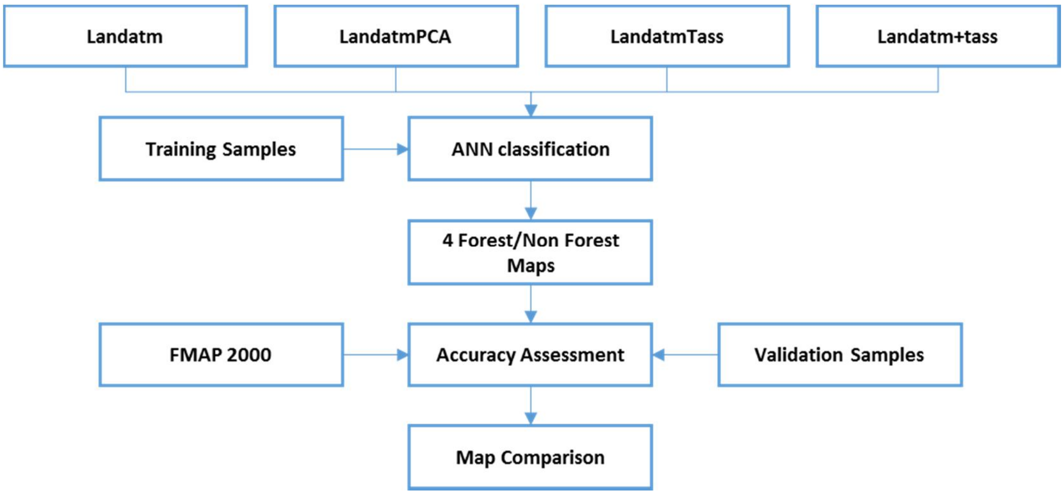

Fig. 3. Methodology Flowchart

Classification. The ANN model used was the multi-layer perceptron, trained by the algorithm named 'back-propagation'. The basis of this algorithm is comparing the output of the ANN with the actual output values provided by the interpreter, and finding out which set of weights provide the least errors [25]. According to Atkinson and Tatnall [26], the multi-layer perceptron model is the most frequently used for image classification in satellite remote sensing. The model is provided by the ENVI software (in the present study 4.7 edition was used).

Although many users of ANNs accept the default training parameters and activation functions to work with, it is important to understand that these parameters and functions have significant consequences for the efficiency of the network training [27]. This is the reason why, the classification of each image was performed through a 'trial and error' procedure, aiming at the achievement of the best possible result.

Accuracy assessment. The generation of the validation points for the accuracy assessment of the produced forest/non forest maps was based on the methodology applied also for the generation of the training samples. In this case, 182 points were derived and identified as 'Forest' and 'Non Forest' by an experienced photo-interpreter.

Confusion matrix, a standard method for classification validation [39] was used in this study. This method cross-tabulates labels assigned to pixels by the classifier with labels assigned to the sampling points during field survey or other validation process, using geographic location as the key to cross-tabulation [40]. The matrices built in this study were analyzed with four measures of agreement, namely the Kappa Index of Agreement (KIA) [41], overall (OA), user's (UA) and producer's (PA) accuracy [40].

As mentioned above, the agricultural areas were removed from the study area, due to their spectral similarity to forests. Consequently, in order to assess the performance of ANNs, the agricultural areas were not taken into account. Nonetheless, these areas were eventually added to the produced forest/non forest maps, in order to obtain complete maps of the study area. In this case, the assessment of the final maps is required as well, in order to determine the accuracy of the complete cartographic product achieved by the presented methodology.

The FMAP 2000 was also assessed for its' accuracy, so that it can be compared with the produced maps. Hence, the same set of 182 validation points was used.

The comparison was performed between the FMAP2000 and the complete cartographic products (agricultural areas included) produced by the methodology presented in this study.

Results and Discussion

Forest/non forest maps. Fig. 4 illustrates the map derived from the classification of the three bands produced by the employment of the Tasseled Cap transformation on the Landsat-5TM image (Landatm), which was the most accurate produced in this study (OA=91,76 %). Fig. 5 shows the FMAP 2000, the accuracy of which was compared to the four forest/non forest maps produced using the ANNs.

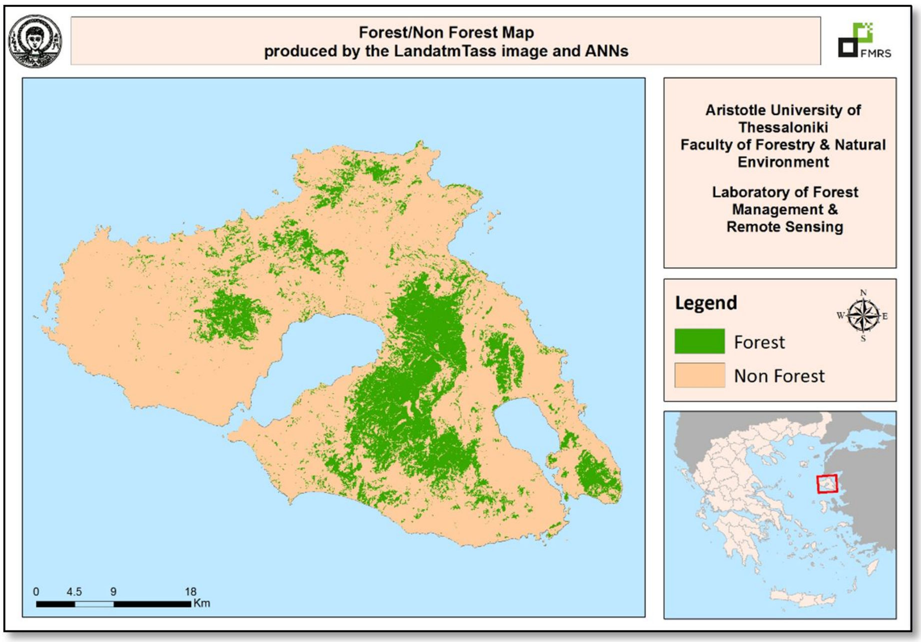

Fig. 4. Forest/Non Forest map produced by the classification of the three bands, derived from the implementation of Tasseled Cap image transformation on the initial Landsat image. It displays with the colors mentioned below the classes: 'forest' and 'non forest' (green= forest, beige= non forest)

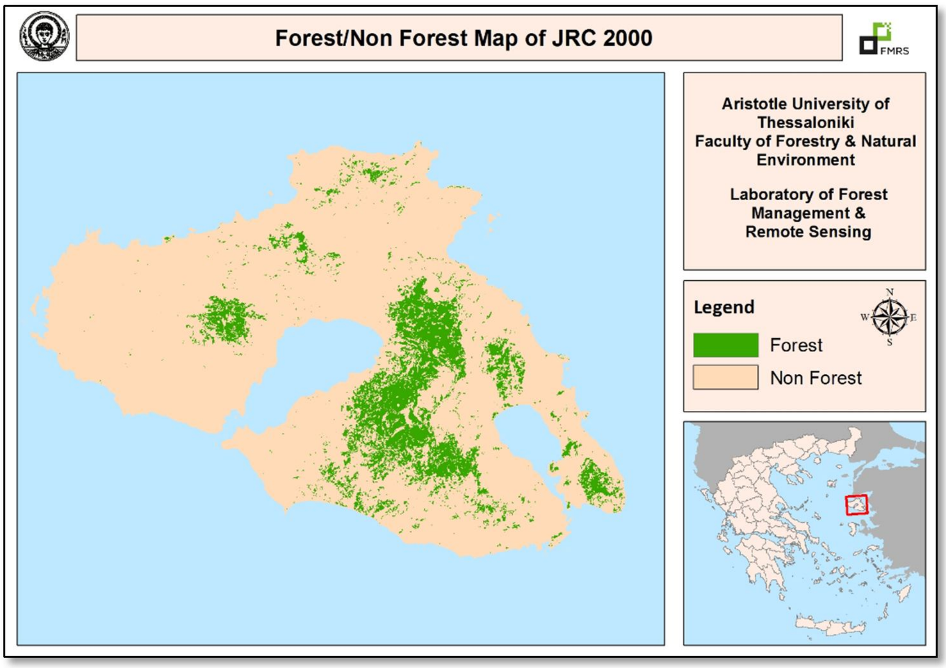

Fig. 4. Forest/Non-Forest map of the year 2000 of the Joint Research Centre (FMAP2000)

Table 1

Overall accuracy, Kappa coefficient, the producer's and user's accuracy for the classes 'forest' and 'non forest' of the produced maps that do not contain the agricultural areas and the JRC Forest Map 2000.

		PA (%)	UA (%)	OA (%)	KIA
Landatm	**Forest**	72,92	87,50	84,17	0,668
	Non Forest	91,67	84,50		
LandatmPCA	**Forest**	77,08	86,05	85,00	0,688
	Non Forest	90,28	86,67		
LandatmTass	**Forest**	83,33	86,96	87,50	0,743
	Non Forest	90,28	90,28		
Landatm+tass	**Forest**	66,67	88,89	82,50	0,628
	Non Forest	93,06	81,71		
JRC Forest Map 2000	**Forest**	52,08	80,65	78,02	0,446
	Non Forest	87,31	84,78		

Accuracy of the produced maps. The results from the accuracy assessment of the produced forest/non forest maps without the agricultural areas, as well as of the FMAP 2000 are presented in detail in Table 1.

Discussion. A closer look at the results of the accuracy assessment presented in chapter 5,2, reveals that in all four cases of classification with the use of ANNs, a production of forest/non forest maps with high accuracy was achieved. Moreover, it is shown that the implementation of the Tasseled Cap transformation on the Landsat image (Landatm) improves the accuracy of the cartographic result by 3,33 %.

More specifically, as far as the classification of the Landsat image (Landatm) is concerned, the accuracies achieved reached 84,17 % OA and KIA=0,668, 72,92 % PA and 87,50 % UA for class 'forest', 91,67 % PA and 84,50 % UA for the 'non forest' class. The examination of the accuracies PA and UA for each class, reveals an underestimation (low PA-high UA) of the class 'forest' and an overestimation (high PA-low UA) of the 'non forest' class. However, the OA (84,17 %) is high, while the value of KIA (0,668) indicates that the agreement between the map product and the reference data is actual and not random. As mentioned in a previous chapter, the agricultural areas, that were initially removed in order to facilitate the classification, were added to the map product for the creation of complete maps of the study area and their accuracy was also assessed. In the case of the classification of the Landsat image, the accuracies achieved for the class 'forest' are 72,92 % PA and 87,50 % UA, for the 'non forest' class 95,52 % PA and 90,78 % UA, while the OA reached 89,56 % and KIA the value of 0,719. Based on these results, the expected increase of the OA, PA and UA for the 'non forest' class is observed due to the rural areas added to the cartographic result.

In the case of the classification of the three components (LandatmPCA), derived from the implementation of the PCA on the Landsat image, the estimated accuracies are 77,08 % PA and 86,05 % UA for the 'forest' class, 90,28 % PA and 86,67 % UA for the 'non forest' class, 85,00 % OA and 0,688 KIA. In this case, the values of PA and UA indicate an underestimation of the class 'forest' and an overestimation of the class 'non forest', while the values of OA and KIA are higher than the ones of the classification of the Landsat image. Furthermore, the accuracies of the complete cartographic product, which includes the agricultural areas, are for the 'forest' class 77,08 % PA and 86,05 % UA, for the 'non forest' class 94,78 % PA and 92,03 % UA, 90,11 % OA and 0,739 KIA.

The third map validated for its' accuracy is the one produced through the classification of the three bands (brightness, greenness, wetness) (LandatmTass), derived from the application of Tasseled Cap transformation on the Landsat image. In this case, it was estimated that for the class 'forest' the PA and

UA are 83,33 % and 86,96 % respectively, for the class 'non forest' the accuracies reached 90,28 % PA and 90,28 % UA, with 87,50 % OA and 0,743 KIA. These results reveal that the classes are neither underestimated nor overestimated, while the OA and KIA are higher than the respective accuracies of the two above-mentioned classifications, indicating the superiority of this map product. Moreover, adding the agricultural areas to the produced map, a complete map of the study area was created, the accuracies of which reached 83,33 % PA and 86,96 % UA for the class 'forest', 94,78 % PA and 94,07 % UA for the class 'non forest', 91,76 % OA and 0,787 KIA.

Finally, the accuracy assessment of the image which includes the six bands of the Landsat image and the three bands derived from the Tasseled Cap transformation (Landatm+tass) revealed that the accuracies reach 66,67 % PA and 88,89 % UA for the class 'forest', 93,06 % PA and 81,71 % UA for the class 'non forest', 82,50 % OA and 0,628 KIA. The significant variation of the PA and UA indicates an underestimation of the class 'forest' and an overestimation of the 'non forest' class. Subsequently, it can be noted that the other three cartographic products outperformed this one agreeing with the findings of Kavzoglu and Mather [32] that the use of additional features in a classification does not always contribute to the improvement of the map product accuracy. Adding to that, the accuracies of the complete map product are 66,67 % PA and 88,89 % UA for the 'forest' class, 96,27 % PA and 88,97 % UA for the 'non forest' class, while the OA is 88,46 % and KIA 0,680.

Based on the above, this study shows that the higher-order features contributed to the improvement of the map product's accuracy, except from the classification of the image, which includes the six bands of the initial Landsat image and the three bands derived from the Tasseled Cap image transformation. Although all four maps produced were of high accuracy, the image which was classified more accurately was the one with the three bands derived from the implementation of the Tasseled Cap transformation on the initial Landsat image.

The FMAP 2000 was also validated in order to be compared with the Forest/Non-Forest maps produced in this study. The results showed that the OA of the map is 78,02 % and the KIA 0,446, while the PA and UA for the 'forest' class is 52,08 % and 80,65 % respectively. Furthermore, for the 'non forest' class the PA reach 87,31 % and the UA 84,78 %. The results reveal that the FMAP 2000 extremely underestimates the 'forest' class in the specific study area. In addition, the Kappa coefficient indicates that the agreement between the map product and the reference data is random.

Finally, the comparison of the FMAP 2000 with the forest/non forest map produced in this study leads to the conclusion that the accuracy of FMAP 2000 is noticeably lower, taking into account not only the OA, but the PA and UA for each class and the value of KIA, as well. The difference in detail and, consequently, in the accuracy between the produced maps and the FMAP 2000 is considered as a logical outcome, due to the large difference of the product's coverage. Therefore, it is illustrated that the production of new Forest/Non-Forest maps offers a better solution than using the already available cartographic product of the JRC, in cases where the study area is considerably smaller than the one of the FMAP 2000.

Conclusions. In the present study, a series of issues concerning, mainly, the use of ANNs in forest/non forest mapping were examine. The results of the study lead to the conclusion that the ANNs are suitable for forest/non forest mapping, producing maps of high accuracy, while the use of the Tasseled Cap image transformation contributes to the improvement of the cartographic result. Additionally, the results showed that the implementation of the methodology proposed in the present study area produced forest/non forest maps with higher accuracy than the one of the FMAP 2000.

Summarizing the results of the study, the following conclusions can be drawn:

- the combination of ANNs and Landsat images for forest/non forest mapping of the Island of Lesvos leads to the production of maps of high accuracy;
- the use of higher-order features (PCA and Tasseled Cap) for forest/non forest mapping of the Island of Lesvos with the use of ANNs produces highly accurate maps;
- the combination of the features derived from the Tasseled Cap transformation with the Landsat image using ANNs for forest/non forest mapping of the Island of Lesvos produces maps of satisfactory accuracy;
- the features derived from the Tasseled Cap transformation on the Landsat image in combination with ANNs lead to the forest/non forest map of the highest accuracy, between the examined combinations;
- the implementation of ANNs on the Landsat image, irrespectively of the use of higher-order features or not, for forest/non forest mapping of the Island of Lesvos, lead to the production of highly accurate maps, which outperform the respective accuracy of the FMAP 2000.

Future research could involve the evaluation of the potential of using different higher-order features or satellite image of different sensors for mapping forests and differentiating them from non-forested areas with the use of ANNs.

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Information about the authors

STEFANIDOU Alexandra – Msc Candidate in the Laboratory of Forest Management and Remote Sensing at the Aristotle University of Thessaloniki, Greece. Research interests: land cover/land use mapping, fuel-type mapping, advanced classification algorithms, Object-Based Image Analysis. The author of 1 publications

DRAGOZI Eleni – Ph.D. Candidate, Forestry Department, Aristotle University of Thessaloniki, Greece. Research associate in the Laboratory of Forest Management and Remote Sensing at the Aristotle University of Thessaloniki, Greece. Research interests – burned-area mapping, fire severity mapping, post-fire monitoring, advanced classification algorithms, land cover/land use mapping. The author of 10 publications. E-mail: edragozi@for.auth.gr

TOMPOULIDOU Maria – Forester Msc, Research associate in the Laboratory of Forest Management and Remote Sensing at the Aristotle University of Thessaloniki, Greece. Research interests – Object-Based Image Analysis, fuel-type mapping, land cover/ land use mapping, advanced classification algorithms. The author of 7 publications E-mail: tompmary@for.auth.gr

GITAS Z. Ioannis – PhD in Geographical Information Systems (GIS) and Remote Sensing, Associate Professor with the School of Forestry and Natural Environment, Aristotle University of Thessaloniki, Greece. Research interests – fuel-type mapping, burned-area mapping, post-fire monitoring, the role of forest fire in global climatic change. The author of 54 publications. E-mail: igitas@for.auth.gr

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КАРТИРОВАНИЕ ЛЕСНЫХ И НЕ ЛЕСНЫХ ПЛОЩАДЕЙ С ИСПОЛЬЗОВАНИЕМ LANDSAT TM И АЛГОРИТМА «ИСКУССТВЕННЫЕ НЕЙРОННЫЕ СЕТИ» (ANNs)

А. Стефанидоу, Е. Драгози, М. Томпоулидоу, Я. З. Гитас
Университет имени Аристотеля
54124, Греция, Салоники, P.O. Box 248
E-mail: alexands@for.auth.gr

Ключевые слова: *картирование лесных и не лесных земель; искусственные нейронные сети; трансформация «колпачок с кисточкой»; анализ главных компонент.*

В настоящей работе был рассмотрен ряд положений, которые касаются, главным образом, использования ANNs при картировании лесных и не лесных земель. Индикаторами устойчивого управления в лесном хозяйстве Европы на ландшафтном уровне (MCPFE 2003) являются пространственная структура и общая площадь лесов. Оба эти индикатора важны для принятия решений на уровне (MCPFE 2007), поэтому существует необходимость в своевременной и точной информации об их текущем состоянии. ***Целью*** *настоящей работы явилось исследование потенциала метода «искусственные нейронные сети» (ANNs) при оценке дифференцирования лесных и не лесных земель, а также анализ применимости данных более высокого уровня, полученных по снимкам Landsat-5 TM с целью улучшения производительности классификатора (ANNs). Исходные параметры снимков были преобразованы при помощи инструментов трансформации изображений: «колпачок с кисточкой» (Tasseled Cap transformation) и анализа главных компонент (Principal Component Analysis, PCA). Исследования проводились в типичной для Средиземноморья местности на северо-востоке Греции. В результате оценки точности классификации было выявлено, что наиболее точная карта (общая точность – 91,76 %, коэффициент согласованности Каппа KIA=0,787) была создана с использованием метода ANNs на основе трёх изображений преобразованного методом «колпачок с кисточкой» снимка Landsat-TM. Сравнение полученной карты с общеевропейской картой лесного покрова 2000, разработанной Объединённым исследовательским центром (JRC) в 2000 году (FMAP 2000), показало, что общая точность классификации этой карты (OA=78,02 %, KIA=0,446) ниже, чем точность карты, которая была создана при помощи метода «искусственные нейронные цепи» (ANNs). Результаты исследования позволяют сделать вывод о том, что ANNs подходит для картирования лесных и не лесных земель, создания карт высокой точности, кроме того использование преобразования «колпачок с кисточкой» позволяет улучшить результаты картирования. По итогам работы были сделаны следующие* ***выводы****: комбинирование метода ANNs и снимков Landsat для картирования лесных и не лесных земель позволяет создавать карты высокой точности; использование данных более высокого уровня (анализа главных компонент (PCA) и преобразования «колпачок с кисточкой») для картирования лесных и не лесных земель с использованием ANNs позволило создать карту высокой точности греческого острова Лесбос; комбинирование параметров изображения Landsat, полученных на основе трансформированного метода «колпачок с кисточкой» и метода ANNs для картирования лесных и не лесных земель острова Лесбос, позволило создать карту приемлемой точности. Результаты исследований показали, что внедрение предложенной в настоящей работе методики создания карт лесных и не лесных земель позволяет получить карты более высокой точности, чем FMAP 2000. Дальнейшее исследование может быть связано с оценкой потенциала использования материала высокого порядка или спутниковых снимков, полученных от различных датчиков, для картографирования лесов и дифференцирования их от не покрытых лесом территорий при помощи ANNs.*

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Информация об авторах

Александра СТЕФАНИДОУ – магистр Лаборатории лесоустройства и дистанционного зондирования, Университет имени Аристотеля. Область научных интересов – картирование растительного покрова/ сельскохозяйственных угодий, составление карт полезных ископаемых, алгоритмы прогрессивной классификации, объектно ориентированный анализ снимков. Автор одной публикации.

Элени ДРАГОЗИ – доктор наук, отделение лесоводства; научный сотрудник Лаборатории лесоустройства и дистанционного зондирования, Университет имени Аристотеля. Область научных интересов – картирование гарей, картирование интенсивности развития пожара, мониторинг местности после пожаров, алгоритмы прогрессивной классификации, картирование растительного покрова/ сельскохозяйственных угодий. Автор 10 публикаций. E-mail: edragozi@for.auth.gr

Мария ТОМПОУЛИДОУ – магистр по специальности «Лесоводство», научный сотрудник Лаборатории лесоустройства и дистанционного зондирования, Университет имени Аристотеля. Область научных интересов – объектно ориентированный анализ снимков, составление карт полезных ископаемых, картирование растительного покрова/ сельскохозяйственных угодий, алгоритмы прогрессивной классификации. Автор семи публикаций. E-mail: tompmary@for.auth.gr

Янис З. ГИТАС – доктор философии в области геоинформационных систем и дистанционного зондирования, доцент факультета лесоводства и природной среды, Университет имени Аристотеля. Область научных интересов – составление карт полезных ископаемых, картирование гарей, мониторинг местности после пожаров, роль лесных пожаров в изменении климата. Автор 54 публикаций. E-mail: igitas@for.auth.gr