Forest Mapping and Forest Cover Change Detection in a Mediterranean Area Using Coarse Resolution Data and Advanced Image Analysis Techniques

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Abstract. The aim of this study is to differentiate forest from non-forested areas and to detect changes on the forest cover by using SPOT-VEGETATION (SPOT-VGT) and simulated PROBA-V data (simulated Landsat and MODIS). More specifically, a) three advanced image analysis techniques, namely, Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Object-based Image Analysis – Nearest Neighbourhood (OBIA-NN) are applied on the SPOT-VGT image and the PROBA-V simulated data and their performance is evaluated in differentiating forest from non-forested areas; and b) multi-temporal Principal Components Analysis (mPCA) is applied on the SPOT-VGT image and the PROBA-V simulated data in order to detect and identify changes on the forest cover, due to forest fires, over a period of time. The resulted products from the two sensors are also compared for their ability in detecting changes on the forest cover. The study area is a typical Mediterranean region located in central Greece. Studying the results from the classification accuracies, the SVM classifier produce the most accurate 'Forest/Non forest' maps not only in the case of SPOT-VGT (86.35%, KIA=0.55) but also in the case of PROBA-V simulated Landsat data (71.43%, KIA=0.46). However, in the case of MODIS it is ANN that produced the most accurate 'forest-non-forest' map (89.86%, KIA=0.61). In relation to the detection of changes on the forest cover, the PCA method proves to be quite successful (MODIS 88.26% - kappa 0.63, PROBA-V 75.28% - KIA= 0.58 and finally on SPOT-VGT 74.33% - KIA 0.58). In conclusion, SVM proves to be the best performing classifier in differentiating areas covered by forest from other classes while the PROBA-V sensor proves to detect forest cover changes due to fires with higher accuracy.

Keywords. PROBA-V, forest/non-forest mapping, coarse resolution data, support vector machines, artificial neural networks, maximum likelihood, object-based image analysis.

1. 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]. As a result, national governments are looking for ways to strengthen their forest management policies, in order to preserve sustainability in forest ecosystems [2]. Several policy processes at global (Kyoto protocol) [1], European (EU Forest Strategy, EU Forest Strategy European Union Forest Action Plan etc.) [3] and national level dictate the collection of forest related information [4].

The effectiveness of forest management is highly dependent on the availability of accurate and current information regarding the state 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 (State of Europe's Forest) [2]. Subsequently there is a constant need for the production of up-to date forest cover maps. Forest cover and forest cover change maps are commonly produced at sub-national, national, European and global level [5], [6]. A practical and rather inexpensive solution for the production of such maps constitutes the use of remotely sensed data (RS) [7], [6]. Satellite data from medium (Landsat TM) and coarse resolution (MODIS, AVHRR and SPOT-VGT) sensors have been traditionally used in the field of forest cover mapping [8], [2], [9]. More specifically, in the European region both types of satellite data have been successfully used in a series of forest mapping initiatives. Hence, existing forest maps vary in their level of detail, scale, sources of information used, and target groups [10]. Examples of forest maps covering the whole Europe which were based on the use of coarse resolution remote sensing data include:

- the Forest Map of Europe (ESA, 1992,1993) which was based on 1km AVHRR data
- the Forest Resource Assessment(FRA) 2000 Forest cover maps which were based on 1km AVHRR data (FAO 2001)
- the Tree Cover Project maps produced by the University of Maryland which were based on 1km AVHRR

In addition, there are forest cover maps covering Europe based on medium resolution data such as:

- the JRC pan-European Forest/Non-Forest Maps (FMAP) available for the years 2000 and 2006 at a 25m spatial resolution
- the CORINE Land Cover for the years 1990 (CLC1990), 2000 (CLC2000) and 2006 (CLC2006). The CLC maps were based on computer-assisted photo-interpretation of satellite data (Landsat-25m)

Several studies have proven that the medium resolution data, such as Landsat and SPOT, are best suited for mapping forests status and trends [11]. However the cost and processing requirements involved, especially for forest mapping at large scales (national, continental, global), can be prohibitively expensive [12], [11]. Additionally, repeat image acquisitions in northern countries with short growing seasons and persistent cloud cover can span up to several years [13]. Hence, the need for frequent updates of available forest related information cannot be fulfilled with this type of satellite data. To overcome these limitations, one solution could be the use of timely and low-cost coarse resolution satellite imagery such as MODIS (250m), AVHRR (1km) and SPOT-VGT (1km) [14]. Up until now, most of the studies related to forest mapping, at global and continental scales (thus including areas in Europe), have been based on vegetation indices (VI) derived from AVHRR images [15].

The launch of the PROBA-V sensor is expected to open new perspectives on Earth's surface monitoring. The PROBA-V mission was conceived to ensure users data continuity of VEGETATION-like products and to provide daily global monitoring at 100m to 300m resolution. The PROBA-V mission is expected to bring improvements compared to SPOT/VEGETATION as a result of its higher spatial and temporal resolution [16]. Consequently, forest cover mapping as well as forest cover change mapping at regional and national scale is expected to be performed with higher accuracy and in shorter time intervals.

Up until now, different classification techniques such as unsupervised clustering [10], Support Vector Machines (SVM), Artificial Neural Networks (ANN) [17], [18], Linear mixture models [19] and Decision trees [20] were combined with coarse resolution data for the production of forest cover maps. In addition, different change detection techniques such as the multi-temporal Principal Component Analysis (mPCA) [21], [22], Change Screening Analysis Technique (Change-SAT) [11], Vegetation Indices [23] Image Differencing, Temporal trajectory analysis (spectral profiles), Image regression and others [20] were employed with coarse resolution data in order to detect large scale disturbances on the forest cover.

The potential of MODIS and SPOT- VGT in forest cover mapping and forest cover change detection has been already demonstrated in a number of studies [24], [7]; both sensors have been also used in the Mediterranean region. More specifically, MODIS data has been used for burned area mapping and fire damage assessment [25], [26], vegetation condition monitoring [8] and forest area estimation [27], while SPOT-VGT data has been used for monitoring forest ecosystems at regional scale [28] and forest logging and to assess the forest Gross Primary Productivity [27].

The aim of the present study was to investigate the potential of using coarse resolution satellite imagery and advanced image analysis techniques for forest/non-forest mapping as well as forest cover change detection mapping, in the Mediterranean region. The specific objectives were:

- to investigate the potential of SPOT-VGT, and PROBA-V simulated data (Landsat at 300m and MODIS at 250m) in forest/non-forest mapping by employing Artificial Neural Networks (ANN), Support Vector Machines (SVM), and, Object-based Image Analysis – Nearest Neighbourhood (OBIA-NN) and to evaluate their performance
- to detect and map changes on the forest cover, due to forest fires, by applying mPCA to SPOT-VGT imagery and the PROBA-V simulated data and compare the results
- to perceive the advantages of PROBA-V over the SPOT-VGT sensor in forest/non-forest mapping

Two types of PROBA-V simulated data were used in this work. The first type was based on MODIS 250m images due to the similar spatial resolution of MODIS with the forthcoming PROBA-V sensor, while the second type was based on Landsat data that were simulated at 300m by VITO. In this work, the ‘simPROBA-V’ is used for the Landsat simulated data and the ‘MODIS’ for the MODIS images.

2. Study area-dataset description

The study area is located in the Mediterranean region and more specifically in the central part of Greece (Figure 1). The specific location was selected due to the number and size of the 2007 forest fires which affected this area. The region consists of the counties of Euboea, Phthiotida, Boeotia, Magnesia, West and East Attica. In this region, Mediterranean-type climatic conditions with hot summers and mild winters are characteristically prevailing.

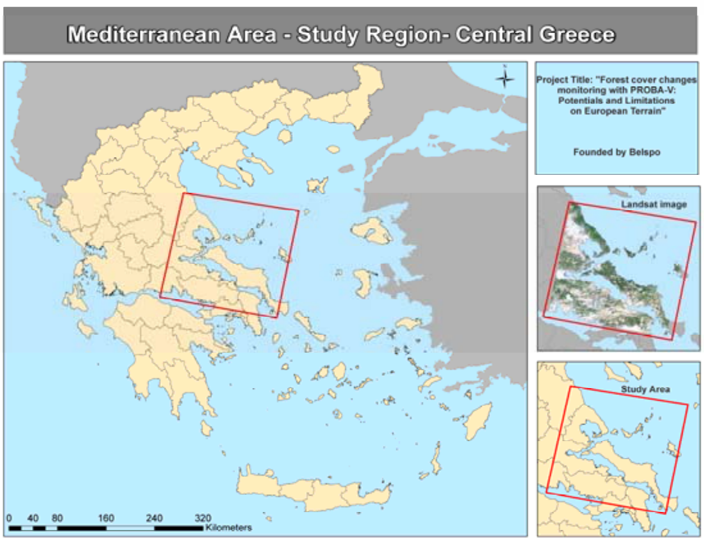


Figure 1: Study area located in Greece.

In this study, six satellite images collected by Landsat 5TM (30m), MODIS (8-day synthesis L3 (MOD09Q1)-250m), and SPOT-VEGETATION (10-day synthesis products (S10)-1km), before and after the 2007 fire events, were used. In addition, the two Landsat images, before and after the fire events were simulated by VITO in order to match the PROBA-V spatial resolution and used in this study. The Landsat images were also used during the analysis for generating reference data for all sensors.

In order to assist the classification and validation processes, auxiliary data such as the JRC 2006 ‘Forest/Non Forest Map’, the 2009 LUCAS (967) (Land Use/Cover Area frame statistical Survey) data and an independent set of visually interpreted set of sample points (300) were also used. The photo-interpretation of the validation datasets was based on autopsies, photographs and reference points gathered in the field (this work was also conducted during the project ‘Forests Future’), and photointerpretation of the Greek Cadastre (constituted by ortho-rectified aerial photos (2007 to 2009)) and Google Earth. Additional auxiliary data used in the procedure were the LPIS data for Greece and Land-cover of 2007, which was produced within the Forests Future project (WWF-Hellas).

3. Dataset pre-processing

Data pre-processing involved the atmospheric correction of the Landsat imagery using the COST method [29]. Following, the simPROBA-V data were further pre-processed in order to become suitable for classification. This included the identification and extraction of the common area among all the Landsat bands and their geometric correction. Finally, the MODIS and SPOT-VGT data were pre-processed in order to remove the bad pixels (clouds etc.) and the values from the resulted products were converted from scaled reflectance into reflectance.

4. Methodology

The methodology involved two stages. The first stage included, classification of the forest and non-forested areas in each satellite image before the forest fires, using advanced image analysis techniques and validation of the derived map products. The second stage involved the detection of the burned areas in each sensor using the mPCA and validation of the final map products. In the second stage both images before and after the fire events, for each sensor, were used during the analysis. These stages are discussed below.

4.1. Forest/non-forest mapping

The two classes of interest namely, ‘forest’ and ‘non-forest’ were identified and characterized based on the JRC definition. Subsequently, a general classification scheme was developed and applied in all sensors. The first step of the methodology was the production of reference data, based on the Landsat image, which would provide the basis for the generation of separate training and validation data sets for each of the 3 satellite images used in this study. In achieving this goal the Landsat imagery needed to be classified into two classes, namely, ‘forest’ and ‘non-forest’. In order to train the classifier and validate the classification product, two set of points were generated through stratified random sampling over the JRC Forest Cover Map 2006; one set with 400 points (Set-1) which was used for training and one set with 300 points (Set-2) which was used for validation. The points were identified as ‘forest’ or ‘non-forest’ using the JRC Forest Cover Map 2006, and photointerpretation based on the Greek Cadastre (aerial photos) and Google Earth images. The identification of the points was made within a radius of 75 meters since the characterization of each point depends on the percentage of forest cover inside this area. After that, Landsat imagery was normalized and classified using the SVM classifier. The derived Landsat forest/non-forest map was validated using two sets of validation points, namely, LUCAS (968 points)(Set-3) points and the visually interpreted set of (300) points.

In the following step, the Landsat classification product was down-sampled to 10 meters and then aggregated to 250, 300 and 1000 meters, to match the resolutions of MODIS, simPROBA-V and SPOT-VGT respectively. The purpose of the aggregation in those three resolutions (250, 300, and 1000) was the creation of separate 'ground truth' (reference) data for each sensor, which would contain sub-pixel information on the percentage of forest cover. In order to generate training and validation points for the different sensors, the points (validation and training) used in the Landsat classification procedure were relabeled, using information from the aggregated maps (including degree of forest cover).

Only in the case of SPOT-VGT, in order to take into account the neighbouring pixels and accommodate any geo-rectification errors, a mean filter (3x3 kernel) was applied on the Landsat aggregation file (1000m) and the SPOT-VGT image. The product resulted from the Landsat filtered aggregation file was used for labeling the SPOT-VGT's training and validation points. The filtered image was also used for the collection of the spectral signatures which were used during the classifications with ANN and SVM. On the contrary, in the case of the SPOT-VGT OBIA classification we used the points (training and validation) which were relabeled using the information from the aggregation file before the application of the mean filter. Continuing, the three classification methods, namely, SVM, ANN and OBIA were applied on the SPOT-VGT, simPROBA-V and MODIS data.

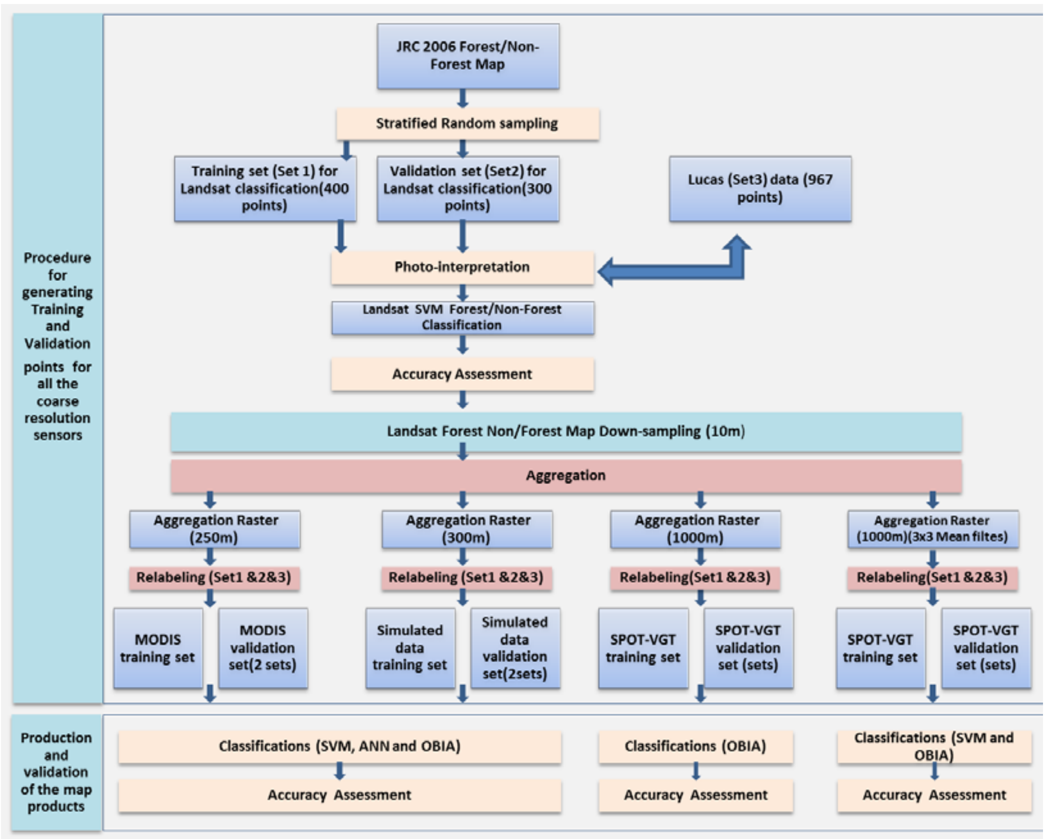


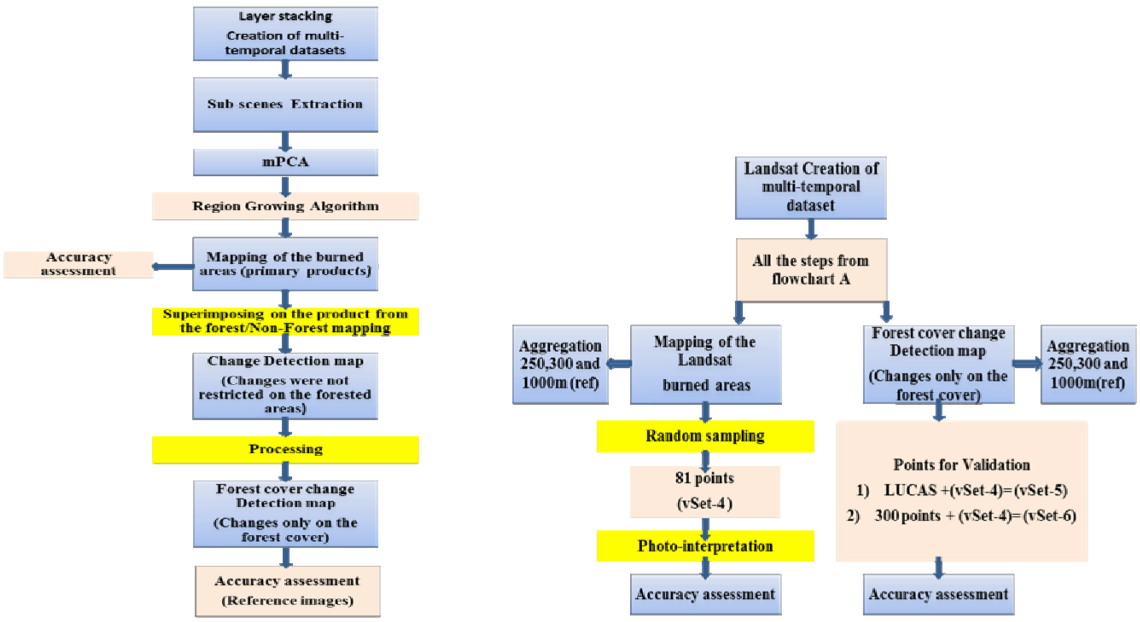
Figure 2: Methodology flowchart for forest/non-forest mapping (General Scheme).

4.2. Forest cover change mapping

In order to evaluate the potential of each sensor in detecting forest cover changes, the mPCA [30] was applied (in all satellite images). Initially, the satellite images before and after the fire events, for each different sensor (SPOT-VGT, simPROBA-V and MODIS), were stacked into one image to form three new multitemporal datasets. In the following step, for each of the multitemporal dataset, subscenes from the areas where changes occurred were visually detected and extracted. Subsequently, the mPCA was applied in each subscene and the PCA component which exhibited the best discriminating ability, was selected and used for mapping the areas affected by fires. Next, the areas where changes occured were mapped (primary products) using a region growing algorithm .

The changed areas (primary products) derived from the aforementioned procedure were superimposed on the forest/non-forest classifications which achieved the greatest accuracies (between different classifiers) in each sensor. Changes displayed on the resulted maps were not restricted within forested areas. The derived map products were further processed in order to produce maps (change detection maps) which would display only the changes on the forest cover (Figure 3a). Afterwards, in order to evaluate the accuracy of the change detection maps (forest/non-forest/changes in forests) derived from the SPOT-VGT, simPROBA-V and MODIS data, 'ground truth' images were produced. The production of reference data was again based on the Landsat images. More specifically, the mPCA was applied in the Landsat images and the areas where changes occurred were mapped using the same way as in the case of SPOT-VGT, simPROBA-V and MODIS. Eventually, the Landsat change detection map was produced with the same way as the change detection maps from the coarse resolution data (Figure 3b).

The Landsat change detection map obtained from the previous procedure was evaluated for its accuracy. In order to evaluate the Landsat map products, an extra set of 81 points (vSet-4) was generated with stratified random sampling inside the mapped burned areas and added to the existing validation sets (LUCAS plus 81 points (vSet-5) and 300 points set plus 81 points (vSet-6)). Then, according to the methodology, all the aforementioned validation sets were visually interpreted. At first, the extra set of 81 points was used to evaluate the accuracy of the change areas (only class change) directly derived using mPCA and secondly the other two sets of validation points (vSet-5 and vSet-6) were used for the evaluation of the final Landsat change detection map. Both files, Landsat changes (only class change) derived by mPCA and Landsat change detection map were aggregated into three spatial resolutions, namely, 250, 300 and 1000. The aggregated Landsat products were used as reference images for evaluating the accuracy of the PCA derived burned areas and the produced change detection maps, of each coarse resolution sensor.



(a) (b)

Figure 3: (a) Flowchart for mapping forest cover changes, (b) flowchart for the generation of the reference data.

5. Results and discussion

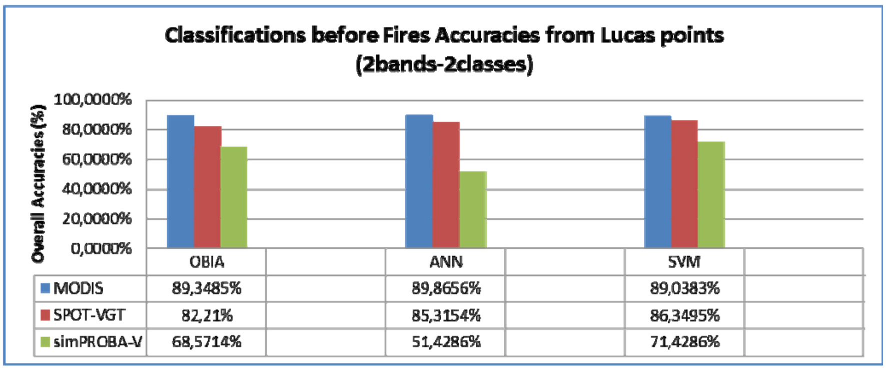
5.1. Forest/non forest mapping

In order to assess the accuracy of the forest/non-forest Landsat map (used for reference data generation) we used two sets of validation points, one independent set of 300 points (Set-2) and the LUCAS data (Set-3). The results showed that using the set of 300 points the overall accuracy achieved, was 88.33% (KIA=0.732) (User's Accuracy) and using the LUCAS data the respective accuracy was 93.17% (KIA=0.579) (User's Accuracy). Subsequently, the results from the accuracy assessment of the Forest/Non Forest map products derived from the SPOT-VGT, simPROBA- V (and MODIS data, are presented in the first graph (Graph 1). The results presented in the first graph were obtained using the relabeled LUCAS data.

Studying the accuracies of the SPOT-VGT, simPROBA-V and MODIS Forest/Non Forest classifications; we conclude that in general SVM performed better than the other classifiers in Forest/Non Forest mapping. More specifically, SVM proved to produce more accurate pre-fire 'Forest/Non forest' maps, in the case of SPOT-VGT (86.35%, KIA=0.549) (User's Accuracy) and PROBA-V (Landsat) (71.43%, KIA=0.466) (User's Accuracy). However, in the case of MODIS, ANN produced the most accurate 'Forest/Non forest' map (89.86%, KIA=0.605) with OBIA and SVM producing maps of nearly the same accuracy as ANN.

In all cases, the classification accuracies were highly dependent on the quality of the reference data, as originally expected. The results from the validation of the forest/non-forest maps, revealed that the simPROBA-V and MODIS maps were more accurate in comparison to the SPOT-VGT map products respectively. However, the best classification method varies per sensor. Still, in all cases the increased spatial resolution gave better results.

The fact that our study area is characterized by high spatiotemporal heterogeneity, typical in Mediterranean vegetation patterns, is of great importance for the attribution of these findings. According to literature, overestimation of dominant land-cover is higher in the highly heterogeneous landscape mosaic with complex shapes of patches [31]. More specifically when the satellite images are degraded to coarser spatial resolutions, the proportion of the dominant land-covers exhibits a rapid increase and is prone to be strongly overestimated at the coarser levels of spatial aggregation at the expense of non-dominant land-covers. This result shows that dominant land-cover classes are progressively overestimated with decreasing resolution due to spatial mixing of land-covers. [32], [31], [33], [34]. Moreover the fact that SVM, in most cases, exceeded in performance the other classifiers can be attributed to the fact that SVM was specifically designed for binary problems [16]. Moreover the applications of SVM in several studies have shown that his performance is better than the other classifiers or at least equally well [35]. So it was expected that the classifier would exceed high or at least equally performance with the other classifiers in the forest/non-forest classification problem.



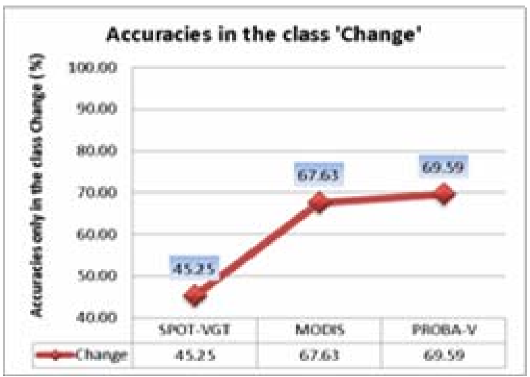
Graph 1: Forest/non-forest classification accuracies using LUCAS data.

5.2. Forest cover change mapping

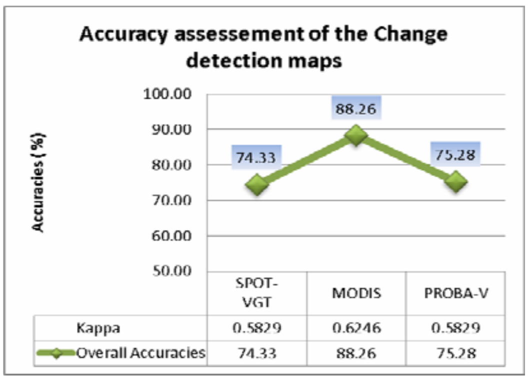
In order to assess the results after the mPCA procedure, two accuracy assessments were conducted. Initially, the accuracy of the products (only class change) directly derived from the mPCA procedure (primary products) was assessed and secondly the accuracy of the final change detection maps. The ability of each sensor to detect changes regardless of the land cover which altered was assessed by estimating the accuracy of the primary products. The results from the aforementioned procedure are presented in the Graph 2(a). The results from the accuracy assessment of change detection maps, per sensor, are presented in the Graph 2(b).

The results in the Graph 2(b) indicate that forest cover changes were detected successfully in all cases by the applied change detection method. More specifically, the results in the change detection Landsat map showed that using the validation points from vSet-6, the overall accuracy achieved was 90,33% (KIA=0.732) (User's Accuracy) while the overall accuracy achieved using the vSet-5 was 92.37% (KIA=0.657) (User's Accuracy). Especially, for the Landsat change detection map, which was evaluated with vSet-5, the User's Accuracy achieved inside the class of interest 'Change' (forest cover change) was 70.37% and the Producer's Accuracy 97.44%. Continuing in the case of MODIS, the achieved Overall Accuracy was 88.26 %(KIA= 0.624) (User's Accuracy) whilst in the class of interest (forest cover change) the achieved accuracy was 67.63% (User's Accuracy). Additionally, the achieved overall accuracy on the PROBA-V (Landsat) change detection map was 75.28 % (KIA=0.582 (User's Accuracy) and 69.58% (User's Accuracy) in the class of interest, while the achieved overall accuracy on SPOT-VGT change detection map was 74.33% (KIA =0.583) (User's Accuracy) and 47.25% (User's Accuracy) in the class of interest.

A closer examination of the results revealed that in all cases apart from the simPROBA-V data, the method failed to detect small burned areas. This fact is not new since it is already known that coarse resolution data do not directly allow accurate change area estimation because most of the changes occur at sub- pixel scales [23]. Despite that, the changed areas were mapped to a sufficient degree. Summarizing, the results above indicate that using simPROBA-V data and MODIS in detecting forest cover changes, proved to be more efficient compared to SPOT-VGT. Although it should be noted that the simPROBA-V data cannot give statistically valid results because of the small examined area, the results are better in comparison to SPOT VGT respectively results.



(a)



(b)

Graph 2: (a) Overall accuracies only in the class change, per sensor. (b) Overall accuracies of the change detection maps, per sensor.

6. Conclusions

In this work, SPOT-VGT and PROBA-V simulated data were employed and their potential in forest/non-forest mapping as well as on the forest cover change detection was investigated. In general, it can be concluded that the PROBA-V simulated data produced more accurate maps both in separating forest from non-forested areas, and, in detecting the changes on the forest cover.

Based on the results of this work the following conclusions can be drawn:

- the forest/non-forest maps produced from the use of the PROBA-V simulated data were of higher accuracy when compared to maps produced from SPOT-VGT imagery
- SVM proved to be the best performing classifier in differentiating areas covered by forest from other non-forested areas in the case of SPOT-VGT and simPROBA-V while ANN was the best performing classifier in the case of MODIS
- the use of PROBA-V simulation data proved to be more efficient in detecting changes to forest cover when compared to SPOT-VGT

Based on the above, the PROBA-V mission is expected to bring significant improvements in forest cover mapping as well as in forest cover change detection in comparison to SPOT-VGT mainly due to the higher spatial resolution of the forthcoming sensor. The use of the real PROBA-V data together with advanced image analysis techniques are expected to improve the quality of existing forest maps at continental and global scale. As a result, the new sensor is expected to offer a new perspective in forest mapping at these scales.

References

[1] FAO, 2011. State of the World's Forests. Food and Agriculture Organization of the United Nations. Rome.

[2] Europe, F., 2011. (SoEF) State of Europe's Forests 2011. Status and Trends in Sustainable Forest Management in Europe. Forest Europe. United Nations Economic Commission for Europe', Food and Agriculture Organization, Oslo, Norway.

[3] The EU Forest Action Plan 2007-20011, available at: http://ec.europe.eu/agriculture/fore/publi/2007_2011/brochure_en.pdf

[4] Häme, T., Aulamo, O., Gallego, J., Hallikainen, M., Kauppi, P., Lahtinen, P., Miller, N., Pulliainen, J., Saari, H., Sephton, T. and others, 2006. Kioto+ mission: Global and accurate monitoring of forest, land cover and carbon, Vol. 559, VTT Technical Research Centre of Finland.

[5] Mulders, M. A., 2001. Advances in the application of remote sensing and GIS for surveying mountainous land, *Int. J.Appl. Earth Observ. Geoinform*. 3 (1), pp. 167–172.

[6] Schuck, A., Päivinen, R., Häme, T., Van Brusselen, J.; Kennedy, P. and Folving, S., 2003. Compilation of a European forest map from Portugal to the Ural Mountains based on earth observation data and forest statistics. *Forest Policy and Economics* 5(2), pp. 187-202.

[7] Potapov, P., Turubanova, S. and Hansen, M., 2011. Regional-scale boreal forests cover and change mapping using Landsat data composites for European Russia. *Remote Sensing of Environment,* 115(2), pp. 548-561.

[8] Alexandridis, T., Gitas, I. and Silleos, N., 2008. An estimation of the optimum temporal resolution for monitoring vegetation condition on a nationwide scale using MODIS/Terra data, *International Journal of Remote Sensing* 29(12), pp. 3589-3607.

[9] Päivinen, R., Van Brusselen, J. and Schuck, A., 2009. The growing stock of European forests using remote sensing and forest inventory data. *Forestry,* 82(5), pp. 479-490.

[10] Päivinen, R., Lehikoinen M., Schuck A., Häme T., Väätainen S., Kennedy P., Folving S., 2001. Combining earth observation data and forest statistics. European Forest Institute.

[11] Fraser, R., Abuelgasim, A. and Latifovic, R., 2005. A method for detecting large-scale forest cover change using coarse spatial resolution imagery, *Remote Sensing of Environment* 95(4), pp. 414-427.

[12] De Luis, M., Francisca, G. and others 2001. Climatic trends, disturbances and short-term vegetation Donoghue, D. 2002. Remote sensing: environmental change. Progress in Physical Geography 26(1), 144.

[13] Waske, B., Benediktsson, J., 2007. Fusion of support vector machines for classification of multisensor data. *Geoscience and Remote Sensing, IEEE Transactions* 45(12): pp. 3858-3866.

[14] Pekkarinen, A., Reithmaier, L. and Strobl, P., 2009. Pan-European forest/non-forest mapping with Landsat ETM+ and CORINE Land Cover 2000 data. *ISPRS Journal of Photogrammetry and Remote Sensing* 64(2), pp. 171-183.

[15] Shoshany, M., 2000. Satellite remote sensing of natural Mediterranean vegetation: a review within an ecological context. *Progress in Physical Geography* 24(2), pp. 153-178.

[16] Vapnik, V., 1995. *The nature of statistical learning theory*. New York, Springer-Verlage.

[17] Huang, C., Davis, L. and Townshend, J., 2002. An assessment of support vector machines for land cover classification, *International Journal of Remote Sensing,* 23(4), pp. 725-749.

[18] Kempeneers, P. Sedano, F. Seebach, L. Strobl, P. and San-Miguel-Ayanz, J., 2011. Data Fusion of Different Spatial Resolution Remote Sensing Images Applied to Forest-Type Mapping. *Geoscience and Remote Sensing, IEEE Transactions on* (99), pp. 1-10.

[19] Foody, G., Lucas, R., Curran, P. and Honzak, M., 1997. Mapping tropical forest fractional cover from coarse spatial resolution remote sensing imagery. *Plant Ecology,* 131(2), pp. 143-154.

[20] Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B. and Lambin, E., 2004. Review Article: Digital change detection methods in ecosystem monitoring: a review, *International journal of remote sensing,* 25(9), pp. 1565-1596.

[21] Eastman, J. R., and Fulk, M., 1993. Long sequence time series evaluation using standardized principal components. *Photogrammetric Engineering & Remote Sensing*, 59, pp. 991–996.

[22] Young, S. S., and Wang, C. Y., 2001. Land-cover change analysis of China using global-scale PathFinder AVHRR Landcover (PAL) data, 1982–92. *International Journal of Remote Sensing*, 22, pp. 1457– 1477.

[23] Jin, S. and Sader, S., 2005. MODIS time-series imagery for forest disturbance detection and quantification of patch size effects. *Remote Sensing of Environment,* 99(4), pp. 462-470.

[24] Wulder, M., White, J., Gillis, M., Walsworth, N., Hansen, M. and Potapov, P., 2009. Multiscale satellite and spatial information and analysis framework in support of a large-area forest monitoring and inventory update. *Environmental Monitoring and Assessment*, pp. 1-17.

[25] San-Miguel-Ayanz, J., Camia, A., Liberta, G. and Boca, R., 2009. Analysis of forest fire damages in Natura 2000 sites during the 2007 fire season. EUR.

[26] Boschetti, L., Roy, D., Barbosa, P., Boca, R. and Justice, C., 2008. A MODIS assessment of the summer 2007 extent burned in Greece. *International Journal of Remote Sensing,* 29(8), pp. 2433-2436.

[27] Maselli, F., Barbati, A., Chiesi, M., Chirici, G. and Corona, P., 2006. Use of remotely sensed and ancillary data for estimating forest gross primary productivity in Italy. *Remote sensing of environment,* 100(4), pp. 563-575.

[28] Guyon, D., Duchemin, B., Lagouarde, J. and Berbigier, P., 2000. Monitoring of forest ecosystems at regional scale using VEGETATION daily-data: First results on the Landes maritime pine forest (SW France). *Proceedings Séminaire VEGETATION*, pp. 119-125.

[29] Chavez, P., 1996. Image-based atmospheric corrections-revisited and improved. *Photogrammetric Engineering and Remote Sensing*, 62(9), pp. 1025-1035.

[30] Vos, L., Moelans, W., Versluys, J., Moreau, V., Jamoye, J., Vermeiren, J., Maresi, L. and Taccola, M., 2010. The Vegetation Instrument for the PROBA-V Mission. Small Satellite Missions for Earth Observation, 301-309.

[31] Lioubimtseva, E., 2003. An evaluation of VEGETATION-1 imagery for broad-scale landscape mapping of Russia: effects of resolution on landscape pattern. *Landscape and urban planning*, 65(4), pp. 187-200.

[32] Hay, G., Niernann, K. and Goodenough, D., 1997. Spatial thresholds, image-objects, and upscaling: a multiscale evaluation. *Remote Sensing of Environment,* 62(1),pp. 10-19.

[33] Mayaux, P. and Lambin, E., 1995. Estimation of tropical forest area from coarse spatial resolution data: a two-step correction function for proportional errors due to spatial aggregation. *Remote sensing of environment,* 53(1), pp. 1-15.

[34] Moody, A. and Woodcock, C., 1994. Scale-dependent errors in the estimation of land-cover proportions: Implications for global land-cover datasets, *Photogrammetric engineering and remote sensing,* 60(5), pp. 585-596.

[35] Mountrakis, G., Im, J. and Ogole, C. 2011. Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*.

[36] Boyd, D. and Danson, F., 2005. Satellite remote sensing of forest resources: three decades of research development. *Progress in Physical Geography,* 29(1), pp. 1-26.

[37] Maselli, F., 2011. Use of MODIS NDVI data to improve forest-area estimation. *International Journal of Remote Sensing*, 32(21), pp. 6379-6393.

[38] Richards, J. A., 1984. Thematic Mapping from Multitemporal Image Data Using the Principal Components Transformation. *Remote Sensing Of Environment,* 16: pp. 35-46.

[39] Wulder, M. A., Kurz, W. A. and Gillis, M., 2004. National level forest monitoring and modeling in Canada. *Progress in Planning*, 61, pp. 365–381.