

MAPPING OF FOREST COVER CHANGE BY POST-CLASSIFICATION COMPARISON AND MULTITEMPORAL CLASSIFICATION OF SPOT DATA – A BULGARIAN CASE STUDY

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Abstract

The paper presents the results of forest cover change mapping in two study areas in Bulgaria (in mountainous and plain-hilly terrain) for period of about 20 years. A comparison was made of two approaches for classification of multitemporal SPOT HRV/HRVIR data with 20 m spatial resolution. The first approach was the post-classification comparison, i.e. pixel-by-pixel comparison of forest/non-forest maps produced by separate classifications of the images from the two ends of the time period. The second approach was a direct multitemporal classification of an image stack comprised of the two-date image data. Following international guidance, instead of counting pixels in the map to obtain the area of forest loss and gain, the areas were estimated by applying an unbiased estimator to sample data collected by stratified random sampling. The map was used to stratify the study areas. Producer's, user's and overall accuracy were also estimated using the sample data. A comparison of accuracy and area estimates, and confidence intervals of estimates, showed that the map produced by direct multitemporal classification was more accurate. It yielded consistently higher class-specific accuracies than the map made by post-classification comparison. As expected, the accuracies of the change classes – forest disturbance and reforestation – were significantly lower than that of the stable classes regardless of the change detection approach. Finally, practical issues and guidelines for future forest change detection studies were discussed.

Introduction

Bulgarian forestry and agriculture have been experiencing transformations for several decades as a result of the transition to market economy, demographic processes, and the adoption of the EU Common Agricultural Policy (CAP). These transformations are accompanied with change in land use and land cover. Abandonment of pastures in mountainous and semi-mountainous regions and their natural reforestation were widespread in 1990s [1]. More recently, the opposite changes may be occasionally observed, namely that young forests are cleared and land is back transformed into pastures, a process which is stimulated by the CAP payments for maintaining pastures in good condition. In the meantime illegal logging increases as well as the development activity in forest areas (e.g. construction of new

ski resorts and facilities) [2]. In addition to these factors, forest disturbance due to wildfires and pest infestation are not uncommon and may affect significant area [3-5].

Mapping of areas of forest cover gain and loss in Bulgaria using traditional forest inventory data is practically impossible because of the lack of archived georeferenced data. Remote sensing is an alternative data source, which provides both high spatial resolution and historical perspective. In this context, the study has been initiated to evaluate the possibilities of using 20 m SPOT HRV/HRVIR imagery for change detection in Bulgarian forests. It was carried out as a pilot study in two test areas and the aim was to provide guidelines for future applications of SPOT data for forest change detection at country level. The SPOT data were selected because of the long image archive dating back to 1980s and the higher spatial resolution as compared to Landsat.

A major concern in every forest change mapping effort is the selection of digital change detection method. A variety of digital change detection techniques utilising satellite image data has become available in the recent decades to monitor ecosystem changes, including forest cover gain and loss [6]. Although sophisticated methods to continuously detect changes over a period of time have been proposed (e.g. [7]) the bi-temporal change detection, i.e. using an image from each end of the time interval of interest, is still widely used when dense image time series cannot be compiled. Two of the most common bi-temporal change detection methods are post-classification comparison (PCC) [8, 9] and multitemporal classification (MTC) [10-12]. The first method involves application of spectral classification on each image independently and then pixel-by-pixel comparison to detect changes in land cover type [6]. The second method applies spectral classification on an image stack, combining data from both dates. The relative performance of the two methods has rarely been evaluated. One example is Mas [13] who compared quantitatively the two methods applying them to Landsat MSS data to map changes in five land cover classes in a tropical region. He found that the post-classification comparison produced significantly higher accuracy than multitemporal classification did. On the other hand, the team led by Olofsson [14], in a comparison of forest cover change maps across Romania, reported considerably lower accuracy due to large commission errors in the map generated by post-classification comparison compared to multitemporal classification. Using simulated data Almutairi and Warner [15] showed that the two methods perform very similarly with the multitemporal classification approach being slightly more accurate.

The objectives of this study are: 1) to assess how accurately forest cover change in Bulgaria can be mapped using 20 m SPOT HRV/HRVIR imagery, and 2) to evaluate the relative performance of post-classification comparison and multitemporal classification as change detection methods. The paper should be regarded as a Bulgarian case study and we do not try to generalize our results regarding the two change detection methods over other regions or image types.

Study area

Two study areas with contrasting physiography and land use patterns are selected (Fig. 1). They represent wide range of conditions in terms of topography, forest types and land-use patterns and are representative for a large part of Bulgaria.

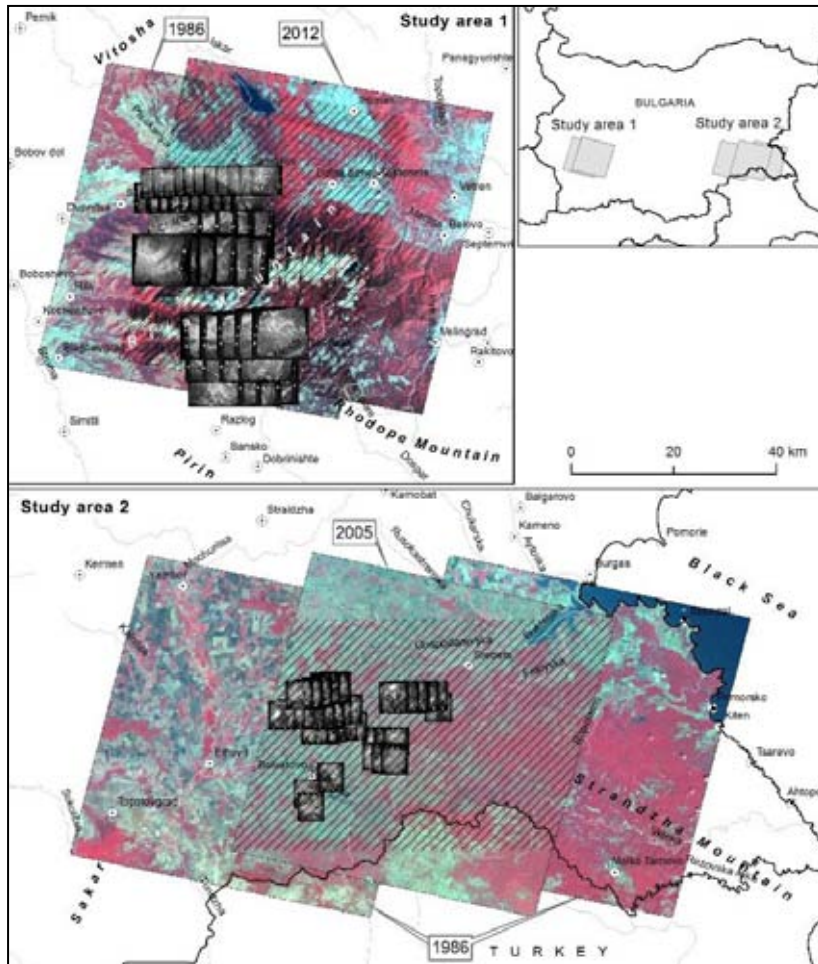


Fig. 1. Maps of the two study areas showing the SPOT imagery and the panchromatic aerial photographs used in the study. The change detection was carried out for the hatched areas.

Study area 1 covers the *Rila Mountains* (2925 m a.s.l.) and the surrounding basins. It features high relief, extensive natural coniferous forests and land use dominated by forestry, nature conservation, tourism, and agriculture. The main

species in the coniferous forests are Scots pine, Norway spruce, and Mountain (dwarf) pine. Steep slopes and deeply incised valleys are characteristic for Study area 1 and allow for testing the change detection algorithms in complicated topographic setting. The main factors for the forest change in the area are timber industry, infrastructure and development projects, including for ski resorts, natural regeneration of trees on abandoned pastures, and wildfires.

Study area 2 is located in the western part of the *Strandzha* Mountains where hilly relief predominates. Forests are mostly broadleaved (Turkey oak, Hungarian oak, *Quercus polycarpa*, etc.) with some sparse coniferous plantations. Agricultural lands are widespread and dominate in the west part of Study area 2. The changes in the forest cover are mostly the result of timber industry (logging and establishment of forest plantations), forest succession on abandoned land, and wildfires. The eastern part of the area is characterized by extensive forests while the western part is more fragmented with land use dominated by agriculture and settlements.

Data and methods

SPOT data

In each study area, changes were investigated using two SPOT images – a base image dated 1986 and a second image dated 2012 (Study area 1) or 2005 (Study area 2) (Table 1). To cover the entire Study area 2, two SPOT scenes were needed in 1986. The scenes were acquired at the same time by the two SPOT 1 HRV instruments. Scenes acquired in the end of the summer (August or September) are used because in this season forest can be easily distinguished from most grasslands and crops. In spring, this discrimination is challenging, particularly for the broadleaved and young coniferous stands. The SPOT data were provided at Level 1A and were orthorectified in ERDAS IMAGINE using ASTER GDEM v2. Firstly, the three base scenes were processed using ground control points (GCP) taken from the 2010 Digital Orthophoto Map of Bulgaria. In Study area 1, GCP measured in the field were also used to check the reliability of the orthophoto map in mountainous area. The number of control and checkpoints and the error of orthorectification are shown in Table 2. The total error for each image is less than one pixel. Secondly, the “modern” scenes in the two study areas were orthorectified using the same (SPOT) sensor model in ERDAS IMAGINE and the same DEM data but the control points were automatically generated by the image-to-image matching module AutoSync and the already corrected base scenes as a reference. Checkpoints were not used and the accuracy not tested. All images were resampled to 20 m using the nearest neighbour method. The SWIR band of the SPOT 4 image (Study area 1) was not used in the analysis.

Table 1. SPOT scenes used in the study

SPOT scene ID	Date	Satellite	Study area
10882658609070929252X	7 Sept 1986	SPOT 1	Study area 1
40892651209240831232I	24 Sept 2012	SPOT 4	Study area 1
10952658608180913511X	18 Aug 1986	SPOT 1	Study area 2
10962658608180913492X	18 Aug 1986	SPOT 1	Study area 2
20962650508120915521X	12 Aug 2005	SPOT 2	Study area 2

Table 2. Results from the orthorectification of the base SPOT scenes. The Root Mean Square Error in pixels for the x-axis (RMSE_x), for the y-axis (RMSE_y), and the total error (RMSE_t) are shown. Errors are calculated using the checkpoints.

SPOT scene ID	Study area	Number of control points	Number of check points	RMSE _x	RMSE _y	RMSE _t
10882658609070929252X	Study area 1	50	8	0.4342	0.3371	0.5496
10952658608180913511X	Study area 2	32	7	0.4663	0.4391	0.6405
10962658608180913492X	Study area 2	33	7	0.2470	0.2240	0.3334

As part of preprocessing the SPOT data, DN-values were transformed to top of the atmosphere (TOA) reflectance using Equation (1):

$$(1) \quad \rho_{\lambda} = \frac{\pi \times L_{\lambda} \times d^2}{ESUN_{\lambda} \times \cos \theta_s},$$

where L_{λ} is the spectral radiance ($W/(m^2 \text{ sr } \mu\text{m})$), d is the Earth-Sun distance for the image acquisition date (astronomical units), $ESUN_{\lambda}$ is the solar exoatmospheric spectral irradiances for each band ($W/(m^2 \mu\text{m})$), and θ_s is the Sun zenith angle. The spectral radiance L_{λ} for each band is calculated using the gain and offset values provided with the image metadata. There one can find also the $ESUN_{\lambda}$ values for the SPOT bands. After the calculation of the TOA reflectance values the radiometric inconsistency between the two 1986 scenes in Study area 2 were much reduced (Fig. 2) and they were mosaicked without further relative normalisation.

Auxiliary image data

High resolution aerial photos were used as a reference data and for collecting training and test datasets for the change detection procedure. To characterize the latter time point, we used the Digital Orthophoto Maps of Bulgaria for 2006 and 2010. The data were available for the entire territory of the two study areas. They represent image tiles in true colour and sub-meter spatial resolution.

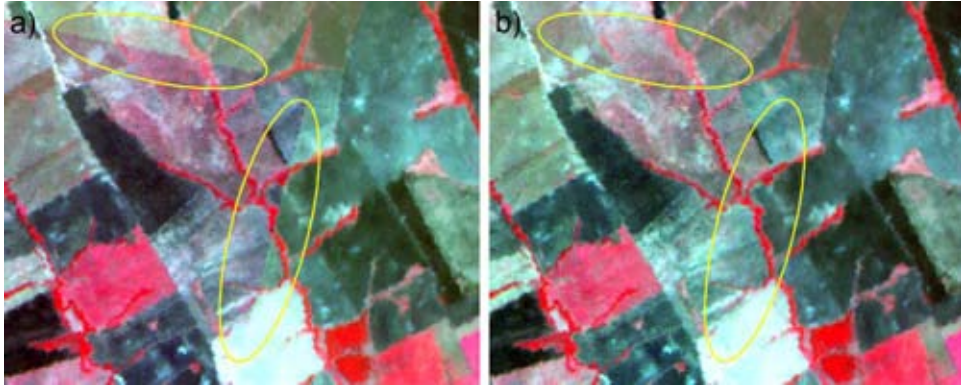


Fig. 2. Excerpts from mosaics of the two 1986 scenes for Study area 2 produced by using a) raw DN data and b) top of the atmosphere reflectance data. The seam line is highlighted.

To characterize the base time point we used archive black and white aerial photographs acquired in 1988 (Study area 1) and 1986 (Study area 2). Unfortunately, these data were available only for part of the territory of the two study areas. The aerial photographs were orthorectified in ERDAS IMAGINE. The coverage of the orthorectified images is shown in Fig. 1. The accuracy of the orthorectified images is summarized in Table 3.

Table 3. Accuracy statistics of the orthorectified black and white aerial photographs

Study area	Photogrametric block number/year	Number of frames	Number of checkpoints	RMSE (m)		
				X	Y	Z
Study area 1	1/1988	11	20 (16)*	2.19	2.47	5.13
	2/1988	21	11	1.49	1.82	6.99
	3/1988	12	17	3.31	4.28	9.72
Study area 2	1/1986	18	16	0.83	1.36	3.09
	2/1986	6	7	0.66	1.17	1.69
	3/1986	6	4	0.58	1.07	2.73
	4/1986	2	2	0.98	0.34	3.13

* the number of checkpoints on the z axis is shown in parenthesis.

Methods

Image classification was selected for the change detection because this method not only can detect changes in the scene but also characterize the type of change. A simple classification scheme with four classes of land cover transition was used: forest disturbance, reforestation, permanent forest, and permanent non forest. The image classification technique is used in two ways in change detection studies. The first approach is the post-classification comparison where the image for each

date is classified separately to produce forest/non forest maps; the two maps are then compared to produce the change detection map. The second approach involves stacking the two images (from the beginning and the end of the period) and classifying them as a single dataset; the change detection map is thus produced in one step. Regardless of the approach the SPOT image data were classified using the Support Vector Machines (SVM) method. The model parameterization and the classification were applied in EnMAP-Box software [16]. The program was set to search for the optimal values of the Gaussian RBF Kernel parameter g and the regularization parameter C . The search range was set initially to $0.001 \div 1\ 500$ and expanded if the number of support vectors was small. The training procedures for the two change detection approaches are outlined in the next sections.

Approach 1: Post-classification comparison

To train the classifier we used a set of pixels collected in two steps. First, each study area was stratified into forest and non-forest using the CORINE Land Cover dataset and 1 000 random points were generated in each stratum. The type of land cover (forest vs. non-forest) for each point and each date was determined through visual interpretation of the auxiliary high resolution image data and the SPOT imagery. To assign the point to one of the classes we visually interpreted the land cover in a square plot with size 40 m centred at the point. The plots which are at the border of forest and non-forest patches were discarded. Using this sample of pixels we performed preliminary classifications and determined regions/land cover types which were incorrectly classified. Based on this knowledge we manually added more points in these problematic regions/land cover types. The reason for this approach is that in order to distinguish between spectrally similar classes the SVM is focusing on the training samples that lie at the edge of the class distributions [17]. That is why we need to provide more training samples representing ambiguous land cover types. The final number of training samples used in each classification is shown in Table 4.

Table 4. Number of training pixels per class for the four SPOT image classifications

<i>Study area</i>	<i>Date (year)</i>	<i>Forest</i>	<i>Non forest</i>
<i>Study area 1</i>	1986	928	832
	2012	1018	764
<i>Study area 2</i>	1986	707	1002
	2005	796	937

To produce the forest/non-forest maps we used the entire sample to train the classifier (Table 4). Then, the same data were used for assessing the accuracy of the individual forest/non-forest maps by applying 10-fold cross validation. For each date and study area we made 10 classifications each time using 90 % of the available

sample for training and the rest 10 % for validation. Pixels used for accuracy assessment are not repeated between iterations. We then calculated the overall accuracy, Kappa, User's accuracy and Producer's accuracy as an average of these measures from the ten iterations.

Finally the forest/non-forest maps from the two time points were compared and forest change maps produced for each study area. The maps were further processed to eliminate class patches smaller than 1 ha. In this way many forest disturbance or reforestation patches, which most probably resulted from miss-registration errors were removed. To estimate the area and accuracy of map categories of the change map, an independent sample was selected by stratified random sample with the strata defined by the map classes. A total of 150 sample units were used in each study area. The number was subjectively chosen and the main criterion was the time needed to collect the reference data for each classification approach and study area (600 sample units in total). The overall sampling intensity was distributed between the classes using Equation (2) [18]:

$$(2) \quad n_i = p_i \times \left(\frac{n}{2}\right) + \left(\frac{1}{k}\right) \times \left(\frac{n}{2}\right),$$

where n_i is the number of points for class i , p_i is the proportion of the mapped area of class i , n is the overall sampling intensity (in this case $n = 150$), and k is the number of classes (in this case $k = 4$). Error-adjusted estimates of the areas of the thematic classes and map accuracy statistics (including 95 % confidence intervals) were produced following the recommendations of Olofsson et al. [14, 19].

Approach 2: Multitemporal classification

In the multitemporal classification, training data for the four classes – forest disturbance, reforestation, permanent forest, and permanent non-forest – were needed. As the territories occupied by the first two classes are small (and unknown) it was not feasible to distribute training pixels randomly. To guaranty that sufficient number of pixels was selected to characterise the small classes we searched the entire study areas systematically and selected training pixels manually. The study areas were covered with 10 km × 10 km grid and within each cell we tried to select a minimum of 4 (maximum 8) pixels from each class. In fact, several cells possessed no forest disturbance or reforestation patches which could be visually identified. As in Approach 1, preliminary classification was performed and additional training samples were added after examining the results. The numbers of training pixels used in Study area 1 were 118, 152, 96, and 116 for permanent forest, permanent non-forest, forest disturbance, and reforestation respectively. In Study area 2 the corresponding numbers were 125, 128, 72, and 102. Similarly to Approach 1, the forest change maps were post-processed in order to remove patches smaller

than 1 ha. The accuracy of the forest change maps was assessed using stratified random sample with the strata defined by the map classes. 150 points (different from those of Approach 1) were used in each study area. The same methods as specified above were used to produce the error-matrix, area estimates, and the accuracy estimates.

Results

Approach 1: Post-classification comparison

The results from the accuracy assessment of the forest/non-forest maps (Table 5) show that the SVM classifier produced very accurate forest/non-forest maps in all four cases. The overall accuracy is between 95 % and 97 % for different dates and study areas. The forest change maps produced by comparison of these forest/non-forest maps are shown in Fig. 3 and the error matrices for the two study areas are presented in Table 6. The overall (error-adjusted) accuracy of the forest change maps is 85 % and 92 % for Study area 1 and Study area 2 respectively. These values are also relatively high, even though they are, as expected, lower than the accuracies of the individual forest/non-forest classifications. The class accuracies, however review more complex picture. The User and Producer Accuracies of the “Permanent forest” and “Permanent non-forest” classes are generally high in the two study areas – between 87 % and 97 %. However the User Accuracy of the change classes – “Forest disturbance” and “Reforestation” is very low, ranging from 50 % to 65 % and the Producer Accuracy is even lower (between 26 % and 52 %). This indicates that the PCC failed to accurately map the forest change. More severe is the problem in Study area 1 where forest disturbance is confused with permanent non-forest and reforestation is confused with both permanent land cover classes (Table 6). Similar is the situation in Study area 2, but here reforestation is mainly confused with permanent non-forest. In fact Producer Accuracies of the change classes are not significant except for “Reforestation” in Study area 2. The high errors for the change classes are likely to result in strong bias of the mapped class areas and this is suggested also from the estimated (error-adjusted) areas, which deviate markedly from the mapped areas (Table 7). It should be pointed out that the confidence intervals of the estimated areas are very wide, which make the estimates not very useful. For the forest disturbance class the estimated areas are not significantly different from 0 (i.e. the margin of error is ≥ 100 , Table 7). The error-adjusted areas of forest change (Table 7) show that reforestation prevails over forest disturbance in both study areas. The reforested area in Study area 1 is estimated to 277 km² (11 % of the area), while in Study area 2 it is estimated to 212 km² (7 % of the area).

Table 5. Results from the 10-fold cross validation of the four forest/non-forest classifications

Study area/Date	Overall accuracy (%)	Kappa (%)	User Acc.		Prod. Acc.		Average number of test pixels per iteration		
			F	NF	F	NF	Total	F	NF
Study area 1									
1986	94.6	89.1	94.9	94.5	94.9	94.2	176	93	83
2012	96.1	91.9	95.6	96.7	97.7	94.0	178	102	76
Study area 2									
1986	97.4	94.5	97.3	97.5	96.3	98.1	171	71	100
2005	97.4	94.7	97.2	97.7	97.1	97.5	173	80	94

Table 6. Accuracy assessment of the post-classification comparison (Approach 1) change maps of the two study areas. The error matrices are expressed as estimated area proportions. Map categories are the rows while the reference categories are the columns. Accuracy measures are presented with a 95% confidence interval. W_i = proportion of area of class i in the map, n_i = number of sample pixels of class i .

	Permanent forest	Permanent non-forest	Forest disturbance	Reforestation	W_i	n_i	User Acc.	Prod. Acc.
Study area 1: Overall accuracy = 0.854 ± 0.058								
Permanent forest	0.480	0.009	0.000	0.046	0.536	58	0.897±0.079	0.927±0.039
Permanent non-forest	0.008	0.328	0.016	0.024	0.376	47	0.872±0.096	0.938±0.057
Forest disturbance	0.005	0.000	0.006	0.001	0.011	20	0.500±0.225	0.258±0.946
Reforestation	0.025	0.012	0.000	0.040	0.077	25	0.520 ±0.2	0.363±0.404
Study area 2: Overall accuracy = 0.918 ± 0.042								
Permanent forest	0.248	0.007	0.007	0.007	0.269	39	0.923±0.085	0.925±0.042
Permanent non forest	0.000	0.624	0.000	0.029	0.653	67	0.955±0.050	0.971±0.025
Forest disturbance	0.003	0.001	0.007	0.000	0.011	20	0.650±0.214	0.504±0.903
Reforestation	0.017	0.011	0.000	0.039	0.067	24	0.583±0.201	0.521±0.441

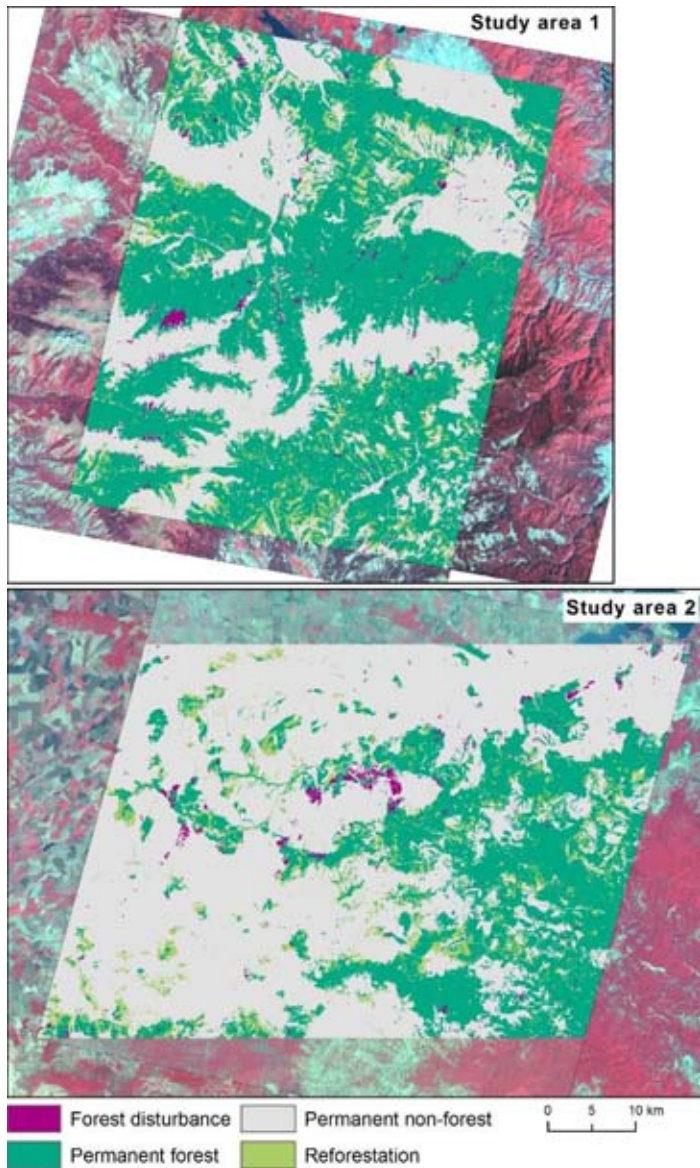


Fig. 3. Forest change maps of Study area 1 (1986 – 2012) and Study area 2 (1986 – 2005) produced by post-classification comparison. Classifications are cleaned-up removing patches smaller than 1 ha.

Table 7. Class areas according to change maps (Mapped areas) and estimated areas with 95 % confidence intervals (CI). Margin of error is the ratio of confidence interval to estimated area expressed as percentage. Map bias is the difference of mapped and estimated area.

	Mapped area [km ²]	Estimated area [km ²]	Map bias [km ²]	± 95% CI [km ²]	Margin of error [%]
PCC Study area 1					
Permanent forest	1336.9	1293.0	44	121	9
Permanent non forest	938.4	872.6	66	107	12
Forest disturbance	27.8	53.9	-26	56	104
Reforestation	193.4	277.1	-84	127	46
Study area 2					
Permanent forest	755.7	753.9	2	74	10
Permanent non forest	1834.1	1804.4	30	105	6
Forest disturbance	30.3	39.1	-9	39	100
Reforestation	189.1	211.8	-23	108	51
MTC Study area 1					
Permanent forest	1269.5	1241.1	28	121	10
Permanent non forest	976.5	912.7	64	117	13
Forest disturbance	27.3	63.1	-36	61	97
Reforestation	223.2	279.6	-56	111	40
Study area 2					
Permanent forest	861.2	897.8	-37	117	13
Permanent non forest	1766.2	1703.5	63	133	8
Forest disturbance	33.8	71.3	-38	68	95
Reforestation	148.1	136.6	12	61	45

Approach 2: Multitemporal classification

Figure 4 shows the forest change maps resulting from the multitemporal classifications. Visually, results are very similar to those obtained with the post-classification comparison approach. A closer look reviews that, in general, forest disturbance and reforestation patches identified by the two approaches spatially coincide, at least for the largest patches. The overall accuracy of the forest change maps is 87 % and 91 % for Study area 1 and Study area 2 respectively (Table 8). These figures are similar to those for the PCC change maps. As may be expected, the pattern of class accuracies for the MTC is the same as that for the PCC with the accuracy of the permanent land cover classes being higher than the accuracy of the change classes. The User and Producer Accuracies of the “Permanent forest” and “Permanent non forest” classes are between 85 % and 96 %. The MTC approach performed better compared with the PCC in terms of accuracy of the “Reforestation” class (from 54 % to 80 %), the measures being significant for both study areas (Table 8).

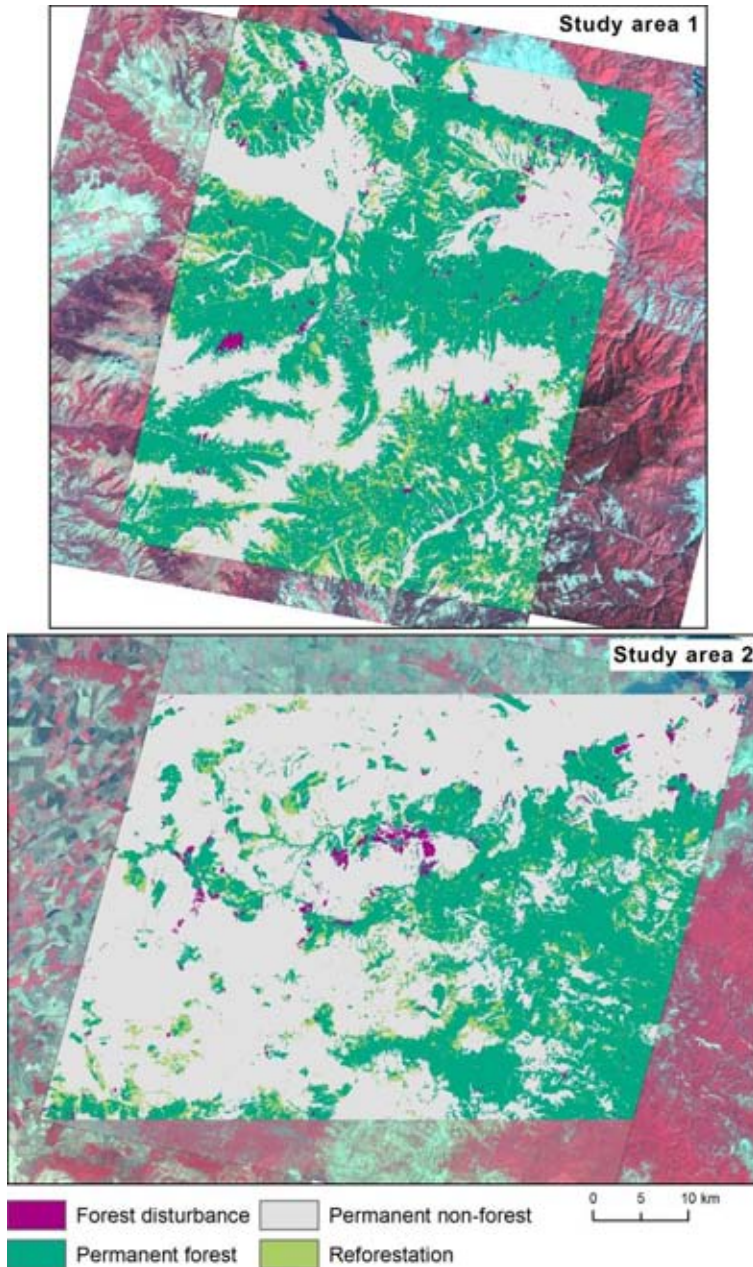


Fig. 4. Forest change maps of Study area 1 (1986–2012) and Study area 2 (1986–2005) produced by multitemporal classification. Classifications are cleaned-up removing patches smaller than 1 ha.

Table 8. Accuracy assessment of the multitemporal classification (Approach 2) change maps of the two study areas. The error matrices are expressed as estimated area proportions. Map categories are the rows while the reference categories are the columns. Accuracy measures are presented with a 95 % confidence interval. W_i = proportion of area of class i in the map, n_i = number of sample pixels of class i .

	Permanent forest	Permanent non forest	Forest disturbance	Reforestation	W_i	n_i	User Acc.	Prod. Acc.
Study area 1: Overall accuracy = 0.867 ± 0.057								
Permanent forest	0.464	0.009	0.009	0.027	0.509	57	0.912 ± 0.074	0.933 ± 0.054
Permanent non forest	0.024	0.334	0.008	0.024	0.391	48	0.854 ± 0.101	0.914 ± 0.060
Forest disturbance	0.002	0.001	0.008	0.000	0.011	20	0.750 ± 0.195	0.324 ± 0.877
Reforestation	0.007	0.021	0.000	0.061	0.089	25	0.680 ± 0.187	0.543 ± 0.342
Study area 2: Overall accuracy = 0.912 ± 0.049								
Permanent forest	0.285	0.015	0.007	0.000	0.307	42	0.929 ± 0.079	0.891 ± 0.092
Permanent non forest	0.029	0.580	0.010	0.010	0.629	65	0.923 ± 0.065	0.957 ± 0.032
Forest disturbance	0.004	0.000	0.008	0.000	0.012	20	0.700 ± 0.206	0.331 ± 0.836
Reforestation	0.002	0.011	0.000	0.039	0.053	23	0.739 ± 0.183	0.801 ± 0.350

Interestingly, the MTC approach confirm that the reforestation in Study area 1 tend to mix with both stable classes, while in Study area 2 it is confused with the permanent non-forest (Table 8). Forest disturbance is, again, the class that is most difficult to map. Even though the results are still unsatisfactory, the MTC performed better than PCC for that class, with User Accuracies over 70 % and Producer Accuracies of 32 %. Note, however that Producer Accuracy are again not statistically significant. The estimated areas of forest change classes are significant (Table 7) but the confidence intervals are quite wide especially for the “Forest disturbance” class. The MTC approach confirm that reforestation prevails over forest disturbance in both study areas. The reforested area in Study area 1 is estimated to 280 km² (11 % of the area), while in Study area 2 it is estimated to 137 km² (5 % of the area). The disturbed forest area is estimated to 63 km² in Study area 1 and to 71 km² in Study area 2.

Discussion and conclusions

With this study, we attempted to test the possibility for automatic change detection and mapping of forest cover change in Bulgaria through satellite image processing. Using satellite imagery for change detection has the advantage of large area coverage but with the drawback of results never being perfect. Classification errors are inevitable in all classifications of satellite data into land surface features but the characteristics of the Bulgarian landscape with its hilly, patchy and varying terrain make it especially difficult to map. The relatively poor classification results for the forest cover change classes in this study proved this. As a result, instead of counting pixels in maps, areas need to be estimated by applying unbiased estimators to sample data of observations of reference conditions on the land surface [14]. *A priori* knowledge of the spatial distribution of disturbance and reforestation in the two study areas suggests that the SPOT-derived classifications managed to detect the main forest change events (for example stand replacing wildfires), but still significant misclassifications were observed. Thus, further improvement is needed to make satellite-derived change detection maps more useful, not only for stratification for reference data collection, but for other spatial analyses too. The main findings from this study and implications for monitoring the state of Bulgarian forests are discussed in the following paragraphs.

The SVM classification method has proven successful in classifying multispectral satellite data. It is particularly suitable for binary problems (like forest/non-forest maps) and, in contrast to the traditional parametric algorithms like maximum likelihood, can handle multimodal classes (e.g. non-forest). The results from Approach 1 suggest that SVM is, in most cases, very accurate in discriminating forest from other types of land cover in the two study areas (Table 5) and this can be attributed to a larger extent to the enhanced parameterization procedure implemented in EnMAP-Box [16], which automatically search for the optimal values of the parameters g and C . However, some misclassification may still be observed even in this “simple” binary classifications. For example in Study area 1 the meadows along mountain river courses stay green in autumn because of the great soil moisture. These wet meadows have similar spectral characteristics to the broadleaved forest and are partly misclassified. Most other grasslands can easily be distinguished from forest in this season because their vegetative growth had already ceased. Another problematic vegetation type is the *Juniperus sibirica* communities above the tree line, which are partly misclassified as forest. In Study area 2, we observed errors in the classification of vineyards. Despite these difficulties, the accuracy of the SVM forest/non-forest maps is generally very high (Table 5). As regards the overall accuracy of the forest cover change maps, these are also relatively high. For Study area 1 maximal accuracy of 87 % was achieved and for Study area 2 the corresponding value was 92 %. These are however overall map accuracies that are not of primary interest in a change detection study. Regarding the two change

classes results are worse. Irrespective of the change detection approach, the “Forest disturbance” class had maximal User accuracy of 75 % and maximal Producer accuracy of 32 % in Study area 1. In Study area 2 these values are 71 % and 50 % respectively. The “Reforestation” class had maximal User accuracy of 68 % and maximal Producer accuracy of 54 % in Study area 1. In Study area 2 these values are 74 % and 80 % respectively. These figures show that: 1) the maximal User accuracies for the two change classes that have been achieved are similar for the two study areas and 2) the Producer accuracy tend to be lower than the User accuracy; it is more variable and, in most cases, unsatisfactory. Similar results to those presented here have been reported in literature, for example Baumann et al. [20]. Their accuracies are, however, slightly higher.

The 20 m spatial resolution of the SPOT imagery used in this study seems to be fine enough to allow for even small patches of stand-replacing change to be portrayed in the images. This is important because in Bulgarian forests changes may occur in many small areas rather than in large clear cuts. This spatial resolution also allows for accurate mapping of forest stand borders even if the forest patches are fragmented and complex in shape (e.g. linear features along roads and rivers). Disadvantage of the SPOT imagery is that their precise georeferencing is challenging because of the difficulties in recognizing ground control points on the image. Table 2 shows that the accuracy of the orthorectified SPOT data is half a pixel. Thus the cumulative positional error produced when two imagery are overlaid is at the magnitude of one pixel. This made the detection of changes in the border areas of forest stands problematic and also leads to a large number of false change detections.

In this study, we used two simple and common change detection approaches, namely comparison of thematic maps from two different time points (post classification comparison) and multitemporal classification. From practical point of view, the first approach is probably to be preferred because it does not use training data for the two change classes. The multitemporal approach may appear more challenging because of the small area of forest change and the difficulty in collecting training data representing forest change. In short, binary classification of forest and non-forest is more straightforward than multitemporal classification where an additional time dimension is introduced. However, both approaches are technically feasible if SVM is used because this classification algorithm does not require large training dataset. Our comparison of the two approaches does not provide a definitive answer which of them is more accurate because the two experiments presented here are not directly comparable (different training data are used in each case including such collected manually). Instead we tried to follow literature-derived good practices (where available) to get the maximum performance of each procedure. For example, the advantage of Approach 1 is that large number of randomly distributed forest and non-forest training pixels can be collected in short time and we used between 700 and 1 000 per class (Kuemmerle et al. [9], for example, recommend using minimum

300 to 500 ground truth points per class). As expected, the class-specific accuracies are quite similar for the two stable land cover classes and considerably higher than the accuracy of the change classes. The multitemporal approach performed better in our study areas as evident by the consistently higher class-specific accuracies of the change classes, but still the Producers Accuracies of the “Forest disturbance” class were not significant. More interesting than accuracy is the uncertainty of the estimates of the areas of forest disturbance and regeneration. The margins of error for the area estimates, defined here as the ratio of the 95 % confidence interval to the area estimate, are smaller when using the change map created by multitemporal classification to stratify the study areas. The area estimates of forest disturbance were not significantly different from zero in neither study area when using the change map constructed by post classification comparison as stratification. All area estimates are rather uncertain with no margin of error being less than 40 % but this is consequence of the small sample sizes in addition to the accuracy of the stratifications. A larger sample would have resulted in higher precision. Note that the change map created by multitemporal classification used much smaller training dataset than that used in the post-classification example. It is fair to assume that had more training data been used with the multitemporal approach the difference in accuracy between the two approaches would have been even greater.

Most forests in Bulgaria are actively managed and regularly inventoried and these activities provide statistical data to assess forested area and its change at national scale. For example, the Executive Forest Agency (EFA) reported increase in forest area from 3.14 million ha to 3.72 million ha between 1965 and 2008 [21], which is an annual gain of 0.42 %. However, the effect of some processes like forest removal by illegal logging and forest establishment on abandoned agricultural land (mostly pastures) may not be well accounted for in the EFA reports. The abandoned pastures are not part of the lands managed by the State Forestry Enterprises and their rate of reforestation is thus poorly known. Other problem is that the inventory information is available mainly on paper [21] and geospatial technologies are not used effectively or not used at all. It is also widely acknowledged that the access of society and the research community to information about forest (e.g. metadata, methodology used to collect information, accuracy assessment of data, etc.) is difficult. Another source of information that can be used to evaluate the changes in forest area is the CORINE Land Cover (CLC) dataset [22]. A shortcoming of the CLC change layer is that the minimum area of detected changes is 5 ha as opposed to 1 ha in this study. The methods tested in this study may complement the existing sources of information and further improve our understanding of the rates of forest change in Bulgaria. Remote sensing data are currently not used for this purpose in a systematic way neither by the national or regional forest authorities nor by the research community. In this context, it is important to evaluate the possibilities and the limitations of using satellite data and estimation techniques for assessing forest change from the perspective of the Bulgarian conditions, i.e. forest types, forestry

practices, land use pattern, etc. By examining the performance of two change detection approaches on two contrasting study areas this paper tries to contribute to the development in that direction. Even though we used SPOT images, the same change detection techniques may be applied with free satellite data like Landsat and Sentinel-2. With the perspective of collecting longer time series of Sentinel-2 data in the coming years, the need of capacity building for processing these data became obvious. Efforts and networks as GOF-C-GOLD, the establishment of good practice guidelines in forest change detection [12], and the availability of free software (e.g. BEEODA, EnMAP-Box) are valuable for the capacity building in Bulgaria.

Based on the experience gained in this study we can formulate several conclusions and guidelines in support of future studies:

- Comparing highly accurate forest/non-forest maps of the same area does not necessarily yield maps of forest cover change of high accuracy – or even accuracy that is significantly different from zero.

- The magnitude of area and accuracy estimates of forest/non-forest maps should not be used to communicate the accuracy and area bias of change maps constructed by post-classification comparison – an independent assessment of the change map is required.

- The multitemporal classification approach yielded maps that were more accurate and stratifications more efficient compared to the maps created by the post-classification comparison. However, the Producers Accuracy of the “Forest disturbance” class was not significant even with the MTC approach. Larger sample, than that used in this study, should be used to assess accuracy of classes with small areas as the “Forest disturbance” in our two study areas.

- Areas of forest disturbance and regeneration estimated by applying a stratified estimator to sample data were all significantly different from zero when the study areas were stratified using the change maps created by the multitemporal approach, even though just 150 sample units were collected.

- Multitemporal classification by non-parametric algorithms of forest change combined with stratified estimation can be easily implemented in open source software, and can help Bulgarian Universities, NGOs, and Government agencies in monitoring forest and collecting independent, statistically sound data of change rates.

- Possibilities to increase the geometric accuracy of the orthorectified SPOT imagery by using higher resolution/more accurate DEM and higher number of GCPs, etc. should be further evaluated.

- Studies that make use of auxiliary information to separate forest from spectrally-similar vegetation classes (including phenological information and expert knowledge, i.e. manual editing of the classification output) should be attempted in search of improvement of the accuracy of satellite-derived forest change detection maps.

- Relying on training/validation data visually interpreted from the SPOT imagery itself is uncertain in many cases; it is very important to have high resolution archive aerial photographs in order to accurately determine the land cover of the training/validation pixels at the beginning of the studied period.

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КАРТОГРАФИРАНЕ НА ПРОМЕНИТЕ НА ГОРСКИТЕ ТЕРИТОРИИ ЧРЕЗ SPOT ИЗОБРАЖЕНИЯ С ИЗПОЛЗВАНЕ НА РАЗЛИЧНИ КЛАСИФИКАЦИОННИ ПОДХОДИ

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Резюме

В настоящето изследване е картографирано изменението на горските територии в два тестови участъка в България (планински и равнинно-хълмист) за приблизително 20-годишен период. Сравнени са два различни подхода при класифициране на мултitemпорални изображения от SPOT HRV/HRVIR с пространствена разделителна способност 20 m. Приложена е спектрална класификация на всяко изображение поотделно и след това са сравнени пиксел по пиксел, за да се открият промените в типа земно покритие („гори” и „извън горски територии”). Приложена е и спектрална класификация директно върху комбинираните данни от двете сравнявани дати. Сравнени са статистическите данни за точността, които показват, че и двата подхода се държат еднакво добре по отношение на общата точност на получените карти на промените (между 85.4 % и 91.8 %). Резултатите от класификациите са доста сходни за двата устойчиви класа земно покритие – „постоянни гори” и „постоянни извънгорски територии”, при които точността е относително висока. Точността на класовете променено земно покритие е значително по-ниска от тази на стабилните класове, независимо от подхода за откриване на изменението. Установи се, че спектралната класификация на комбинираните данни (т. нар. мултitemпорална класификация) се представи малко по-добре в избраните тестови участъци, като показва по-висока точност при класифициране на горските нарушения и участъците с повторно залесяване. Като резултат са дискутирани някои проблеми и са дадени някои препоръки при изследване на изменението на горски територии със спътникови изображения.