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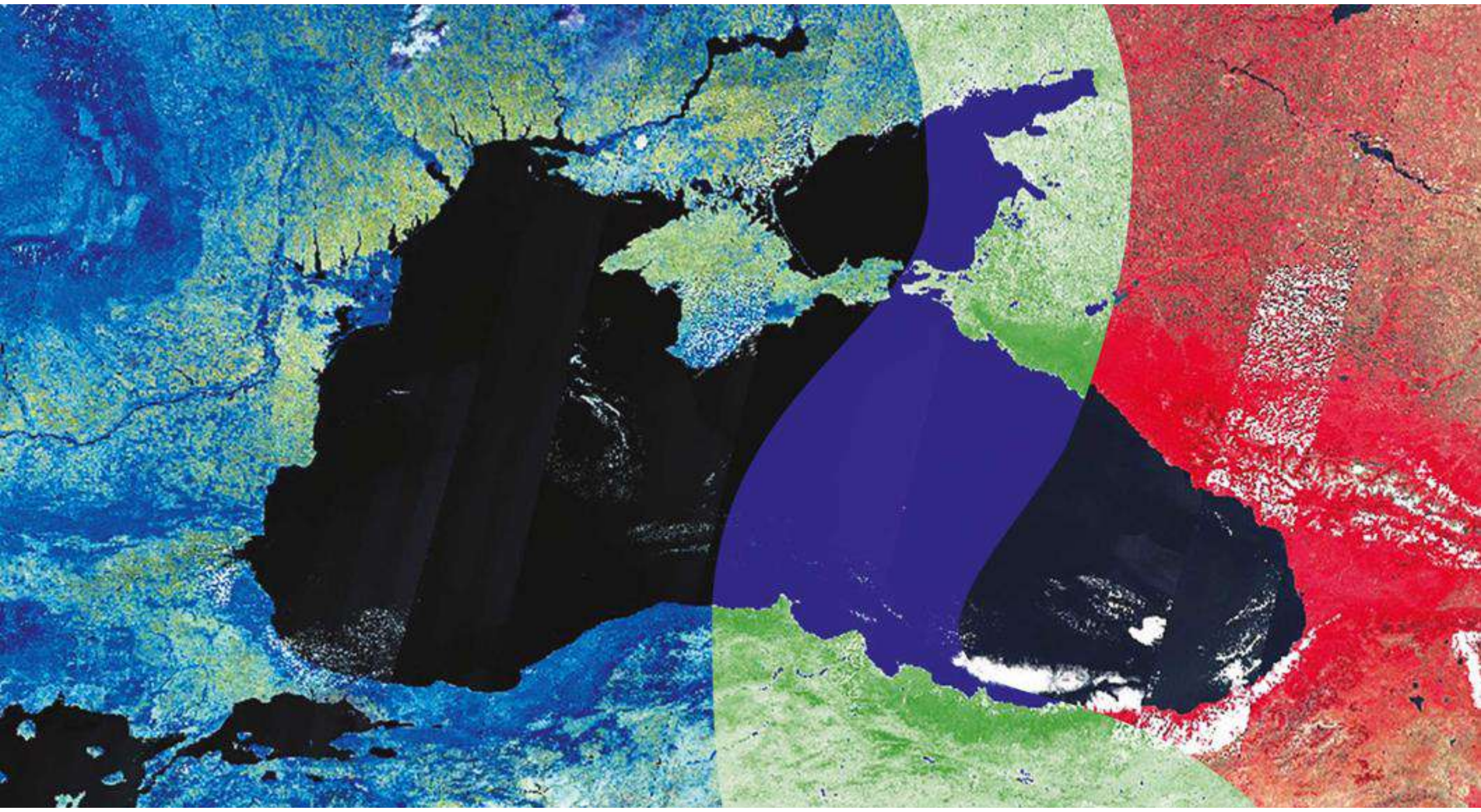

Assessment on forest cover changes and its consequences for the environment

Deliverable D.T1.2.2

Green Alternative

PONTOS-GE (Georgia) – The entire coastline of Georgia & Kolkheti lowland

2022

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Green Alternative, 2022

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List of Abbreviations

B02 - B12	Sentinel-2 Spectral Bands
FAO	Food and Agriculture Organization of the United Nations
GFW	Global Forest Watch
LAI	Leaf area index
MAD	Multivariate Alteration Detection
MMU	Minimal Mapping Unit
NDVI	Normalized difference vegetation index
RGB	Red, Green, Blue
SAGA	System for Automated Geoscientific Analyses
SWIR	Short wave infra-red
WV	World View 2

Introduction

Unsustainable use of forests, uncontrolled and excessive tree cuts, infrastructure projects, mining, intensive grazing, pests, diseases and forest fires are named as the main causes of deforestation and forest degradation in Georgia. The result of this is a significant decrease and degradation of forest area and the latter in itself threatens animal and plant habitats and reduces the ability of forests to provide basic services (IUCN 2021). Deforestation and forest degradation also negatively impact ecosystem services, damage is caused to soil, water balances inside and outside forests, carbon sequestration, and biodiversity (Asner et al. 2009a). It should be noted that in Georgia, as elsewhere in the world, a large part of the population depends on both - wood and non-wood forest resources. According to the National Forest Concept for Georgia, the national forest of Georgia is vital for the security and well-being of the population, as well as for the development of various fields of the country's economy. The forest provides a significant part of the population of Georgia with clean water. Water supply to the sectors of the economy (agriculture, hydropower, etc.) depends on the healthy state of forest ecosystems. Forest determines water quality and reduces the risk of flash floods and floods by regulating surface run-off of sediments. It prevents the development of soil erosion, reduces the risk of landslides, avalanches, and mudflows, and mitigates their impact. By absorbing carbon from the atmosphere and sequestering it into forest mass and soil, the forest plays an important role in the global carbon cycle. These regulatory functions of the forest are important for developing hydropower (a healthy forest reduces river sediments and prevents reservoirs from filling up) and agriculture (protection against soil erosion, pest control, pollination of agricultural crops, etc.). The forests of Georgia are of great aesthetic and recreational value. They have a huge role in the growth of the country's tourism potential and the income associated with this activity. The existence and development of many resorts and various types of tourism depend on forest ecosystems. In addition, the forests of Georgia are of great scientific, historical, spiritual, and cultural significance (The National Forest Concept for Georgia, 2013).

Among different ecosystems, wetland forests are of particular importance as they represent a complex ecosystem and are characterized by unique plant and animal species. A wetland environment creates a precondition not only for biodiversity but is also important for humans whose habitat has expanded rapidly in recent decades and has rapidly invaded biomes it previously avoided. Wetland forests are multifunctional and noteworthy ecosystems for humans. For example, territories covered with wetland forests can conserve and improve water quality, so uncontrolled logging is often a precondition for a significant change (Binkley and Brown 1993). Also worth mentioning are coastal wetland forests and their role in soil stabilization when they stabilize and protect the coastline from erosion by their roots (Gedan et al. 2010). Wetland forests are also known for their ability to reduce flood risks (Acreman and Holden 2013), which is also a prerequisite for human well-being. Thus, assessing the health and sustainability of wetland ecosystems is a major challenge. Despite this, assessing the state of the forest, especially in wetlands, is a difficult task and its assessment by classical methods is not always possible as moving through the forest and conducting field research are associated with huge efforts and financial costs.

To study large areas and hard-to-reach places, remote sensing technology is used which is a particularly practical tool for in-depth assessment and monitoring of processes taking place in the forest ecosystem (Asner et al. 2009b). The rapid development of satellite technologies has led to the ability to assess forests and their structure with high accuracy, for which reason the quality of mapping has significantly improved (McRoberts at al 2010). In addition, the possibility of using free high-resolution satellite multispectral images should be noted. The Sentinel and Landsat missions are particularly famous. For example, free Landsat images have been available since 1972, enabling long-standing data to study forest changes.

Forest changes are mostly characterized by anthropogenic impacts and can be divided into two categories: deforestation when the forest cover is completely reduced in the given area or degradation when the structure of the forest changes and accordingly, its functional abilities change (Hosonuma et al 2012).

Defining reduction or increase in the area covered with trees is not a novelty in the remote sensing field (Hansen et al. 2013). For example, Global Forest Watch (GFW) suggests a global map for forest cover change which is based on Landsat images and hosted on a web portal that allows users to track forest cover change (decrease/increase) throughout the year (Rosi et al 2019). There are also other models, satellite images, and approaches to identify changes in forest cover in landscapes and terrains of different complexity (Giannetti et al 2021; Mikeladze et al 2020). However, despite existing technologies, assessing and mapping the dynamics of wetland forests still remains a technological challenge as the structure of such forests is complex and multilayered and the reduction or growth of trees is difficult to detect from satellites.

Determining forest degradation using satellite images is even more difficult than determining deforestation because forest degradation indicates functional disorders in the forest that are difficult to detect from satellite images. An obvious example of this is the decrease in the density of trees in the forest due to selective cuts when the forest structure is disrupted, but the forest cover is preserved.

The main purpose of this study was to develop and test a satellite-based model of wetland forest change in Kolkheti that would reveal the extent of both deforestation and forest degradation. An important study condition was also to use free, multispectral images of the Sentinel-2 satellite using open-source applications.

Methodology

Pilot Area

Within the framework of the PONTOS Project, Kolkheti wetland forests were selected as a pilot area, which is located between the Enguri and Supsa rivers and extends to the Kolkheti lowland including Katsoburi Managed Reserve. Kolkheti National Park (founded in 1999) is an important part of the pilot area. The area of the Kolkheti National Park is 44960.7 hectares, of which the land area is 29017.7 hectares, and the sea area between the estuaries of the rivers Rioni and Churia is 15877.4 hectares. The following zones have been identified on the territory of the Kolkheti National Park: strict protection zone – 28 035 hectares, of which 15,276 is the water area; managed protection zone - 961 hectares and c) traditional use zone - 15313 hectares. In addition, the territory is protected by the Ramsar Convention (Ramsar site since 1996), and at the same time is Emerald site (since 2018). In 2021, the World Heritage Committee enlisted the Kolkhuri Forests and Wetlands on the UNESCO World Heritage List which represents part of the Caucasus Ecoregion and a global biodiversity hotspot (Mittermeier et al. 2004, Williams et al. 2006).

Kolkheti has a warm temperate climate. Summers are moderately warm (24-25°C) and winters are cool (4-6°C), the average annual precipitation is high and amounts to 1800-2200 mm (Nakhutsrishvili et al. 2011). The humid lowland of Kolkheti is covered by endemic alder forests and the wetlands connected to it (including unique percolating bogs) belonging to the tertiary flora of Kolkhuri refugium (Garsteki et al., 2017) and classified as temperate rainforests (Nakhutsrishvili, Zazanashvili & Batsatsashvili, 2011). Peatlands are closely connected with the forests of the Kolkheti lowland, forming a unified wetland system. In the forest, common alder (*Alnus glutinosa*) grows directly on the swamp, mainly on the wetland territories of *Sphagnum*, sedge, and mixed grasses (Ketskhoveli, 1959). In addition to alder, other plants can be found in forest swamps: *Pterocarya pterocarpa, Frangula alnus, Carpinus caucasica, Ficus carica, Quercus hartwissiana* (Ketskhoveli 1959).

Pre-processing of S2 Products

To ascertain forest changes, two methods were tested: (1) forest cover multispectral classification and (2) Multivariate Alteration Detection. Orthorectified multispectral Sentinel-2A images with 13 spectral bands and a spatial resolution of 10, 20, and 60 meters were used to analyze the changes. The images were downloaded from the Copernicus data portal (https://scihub.copernicus.eu/dhus/#/home). For comparative analysis, the spectral bands of the September 2016 and 2021 images were selected. To improve the quality of the interpretation of satellite images for the spectral bands, an atmospheric correction was performed.

The Sen2Cor tool, a Sentinel-2 Level 2A generation and formatting processor, was used for image atmospheric correction. The reflectance image of the lower 2A level of the atmosphere was developed based on the following parameters: solar zenith angle, sensor viewing angle, relative azimuth angle, surface height above sea level, visibility, and type of aerosols. Parameters were obtained from image metadata, except for altitude and aerosol types, which were determined by specific location. Thus, Sentinel-2 channels were created and prepared for analysis.

Creating Forest Mask in the Pilot Area

Image classification was performed using the Random Forest (RF) algorithm of the SAGA-System for Automated Geoscientific Analyses software. Random Forest (RF), as its name suggests, consists of decision trees that act as an ensemble. Each tree in the Random Forest predicts a certain class, and the class characterized by the maximum score becomes the determinant of the model (Breiman 2001). To train the algorithm, training, and validation data were created. The samples were made by photo interpretation using high-resolution images (Google imagery, World View 2, World View 3) provided in advance by the PONTOS project. In total, 124 training plots were created with a total area of 1439.71 hectares. The training data were categorized into seven land cover classes: bare ground, coniferous forest, deciduous forest, grass cover, and water bodies (lakes and rivers). Agricultural lands were grouped either into the class of grass cover or bare land. As already mentioned, the classification was carried out in two sets, 2016 and 2021, of spectral channels, where the composition of each set was determined by the following channels (B02, B03, B04, B05, B06, B07, B08, B8A, B11, B12). The training data was selected based on the principle that the sample area equally reflected the state of both 2016 and 2021. Samples were not taken in areas, where the land cover category changed over a given time period, for example, forest/grass cover; arable land/forest).

Thus, a full combination of spectral bands was used, where from the most statistically significant variables turned out to be B12 and B11 (see Table 1), which is not surprising since SWIR-shortwave near-infrared channels are known for their good ability to identify (classification) forest species and forest cover (Grabska et al 2019; Immitzer et al 2016).

Variable	Assessment
B12	100.00
B11	80.81
B04	80.64
B07	59.95
B08	51.42
B03	49.96
B06	49.07
B05	47.96
B02	39.31

Table 1. The table shows the importance of spectral variables in the classification and modeling process

In the end, two classified images were created with 7 classes each. During the post-processing, not forest classes were merged, and only two - forest and non-forest area classes were highlighted using classification editing. To generalize the data, forest stand areas were filtered into small clusters of pixels not exceeding 0.5 hectares, as spectral classification errors occurred in smaller forest areas. As a result, we got clearer and cartographically readable data.

Accuracy was assessed with 396 point validation data, which were identified using very high-resolution satellite imagery (Llano 2022), and their number was determined taking into account the area of classification classes (Olofsson et al. 2013). The statistical accuracy of the classification was reflected using a confusion matrix where the overall accuracy for the 2016 image was 0.974 and 0.957 for the 2021 image (see image 1).

Confusion matrix 2016							
		Classified values					
		1 (Not Forest)	2 (Forest)	Total	User accuracy	Total class area (km²)	Wi
Thematic raster	1	237	4	241	0.9834	648.07	0.607
classes	2	6	149	155	0.9612	418.931	0.392
	total	243	153	396		1067.00	
	Producer accuracy	**0.97531**	**0.97386**		**0.9747**		
Overall Accuracy: **0.974**							

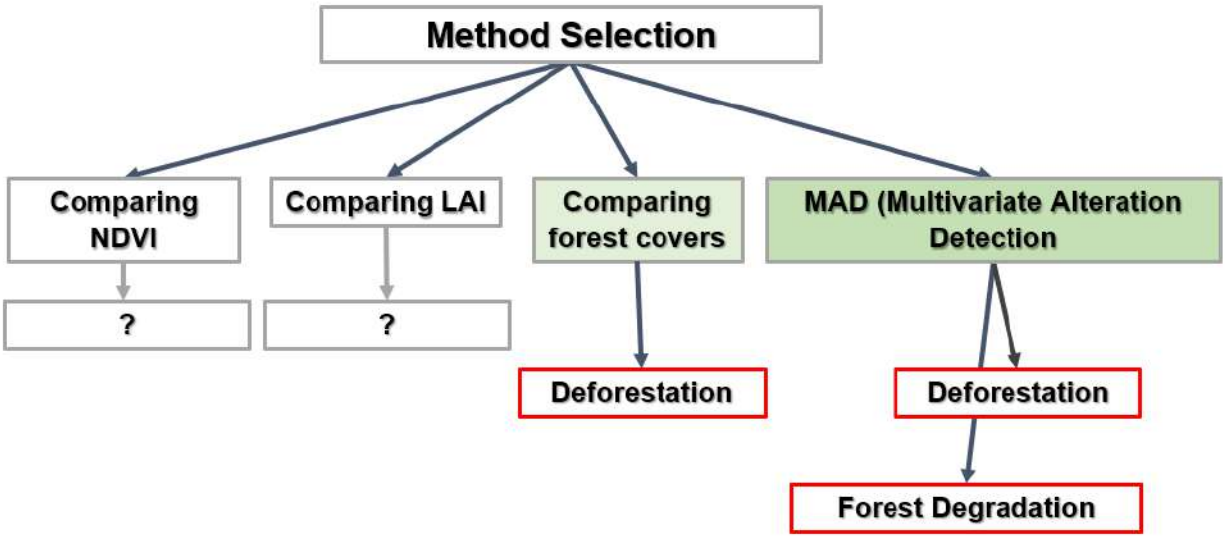
Confusion matrix 2021							
		Classified values					
		1 (Not Forest)	2 (Forest)	Total	User accuracy	Total class area (km²)	Wi
Thematic raster	1	235	10	245	0.9591	645.841	0.605
classes	2	7	144	151	0.9536	421.160	0.394

	total	242	154	396		1067.00	
	Producer accuracy	**0.97107**	**0.93506**		**0.9570**		
Overall Accuracy: **0.957**							

Table 1. The confusion matrix used to assess the accuracy of forest cover classification in 2016 and 2021 is shown on the picture

Multivariate Alteration Detection

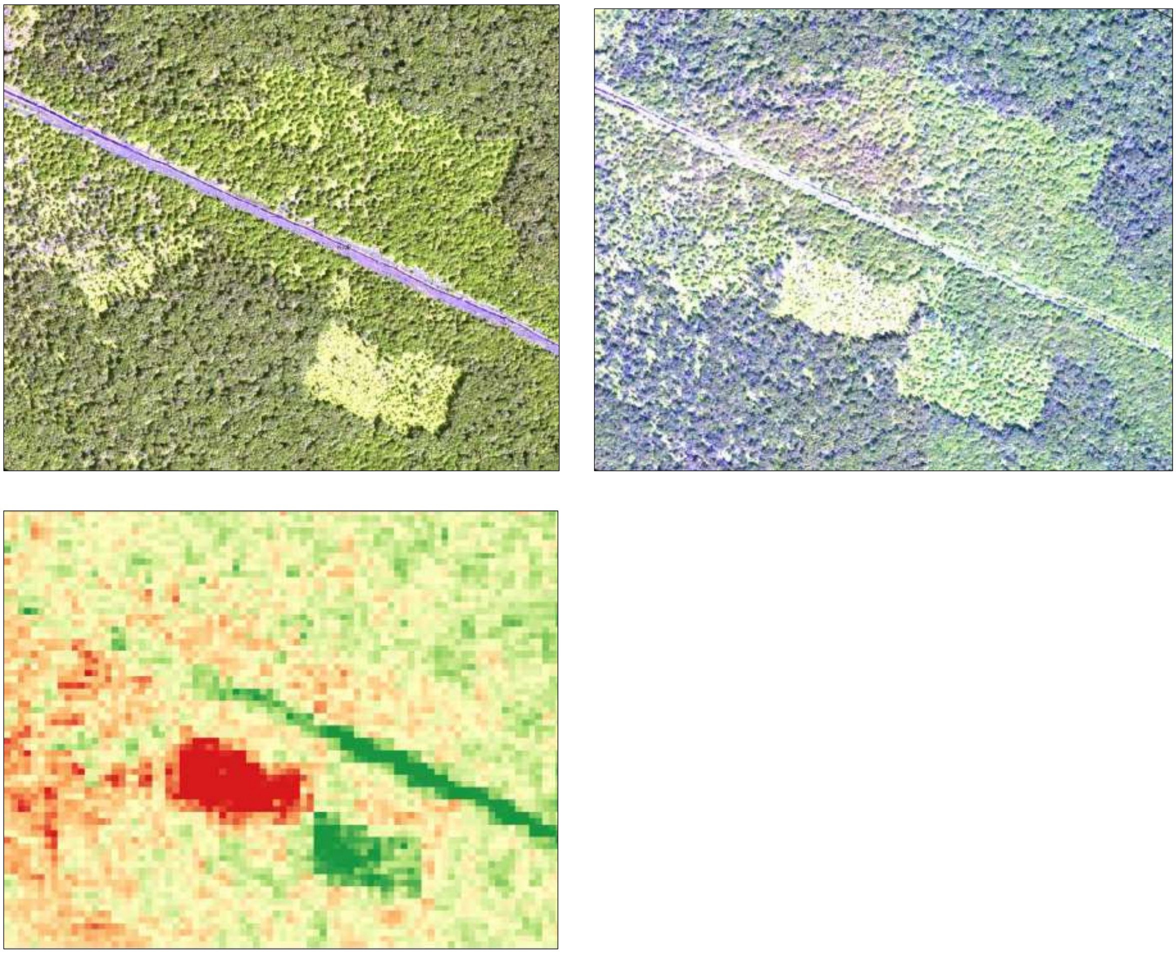
4 methods were tested for determining changes in the forest but only one of them fully reflected the processes taking place in the forest. Images based on NDVI and LAI images did not work because they did not show the changes in the multilayered forests (see Image 2). The best methods were selected by visually comparing the output models with very high-resolution images that clearly showed changes in the forests. Comparing 2016 and 2021 forest cover proved to be semi-useful, as we only got the net loss of trees due to deforestation. The best solution turned out to be the use of the Multivariate Alteration Detection (MAD) algorithm as with the help of this method both areas of deforestation and forest degradation were identified.



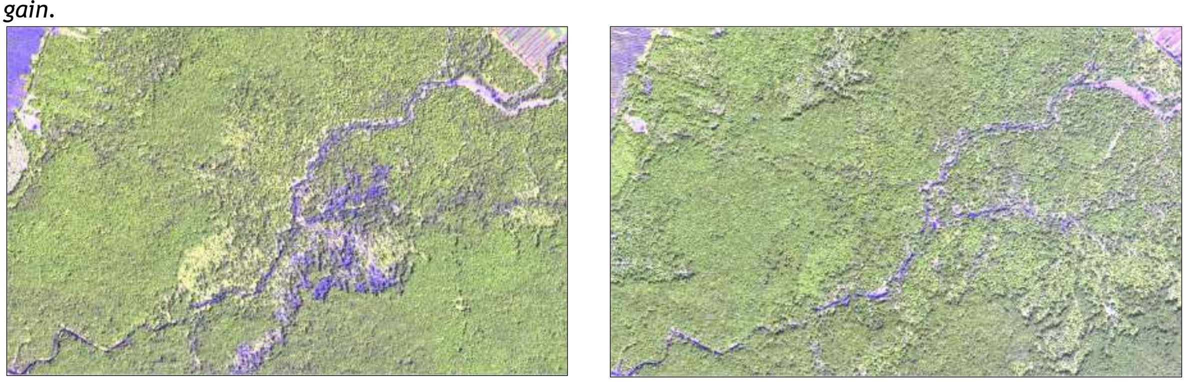
Picture 2. 4 methods to detect changes in the forest and scheme for their selection

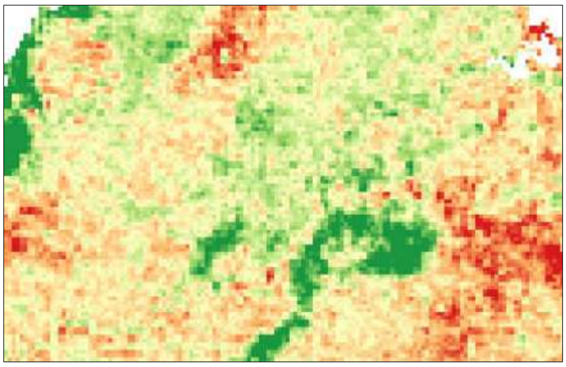
Multivariate Alteration Detection (MAD) algorithm performs change detection between two multispectral images (Nielsen & Conradsen 1998). The MAD algorithm is used for the accurate detection of spatial changes in coherent patterns in satellite images. This method proved to be more effective than other traditional methods. For example, the MAD transformation turned out to be effective for removing incoherent noise from image data and for the detection of anomalies (Nielsen & Conradsen 1998, Nielsen 2007).

The change detection process was performed using Orfeo ToolBox (OTB) 8.0. Comparable images from both 2016 and 2021 were compiled with a set of full spectral bands (B02, B03, B04, B05, B06, B07, B08, B8A, B11, B12). As a result, we got a multi-channel composite image, the channels of which showed the changes in pixel values between 2016-2021. The pixel change gradation ranged from -1 to 1 where negative values were associated with a decrease in tree density and positive values with an increase in tree density. Upon visual inspection, we found that the B12 channel of the received image, compared with other spectral channels, most accurately (did not consider the undergrowth values) showed changes in the forest. The received model was compared with high-resolution *World View 2* images (See Pictures 3-4).



Picture 3. *WV 2016 and 2021 images taken near village Nigvziani (PSh. RGB 6,7,5) above, and the change model obtained by the MAD algorithm of the same area (below), where red pixels show tree loses and green pixels show the gain.*





Picture 4. WV 2016 and 2021 images taken near Churia river (PSh. RGB 6,7,5) above, and the change model obtained by the MAD algorithm of the same area (below), where red pixels show tree loses and green pixels show the gain.

Results

As a result of the processing of spectral images, the following were created: 1) discrete images of forest/not forest covers (forest mask-2016, 2021), and 2) a MAD model with continuous values of forest tree density change between 2016 and 2021.

The forest cover (forest mask) image is binary data represented by just two values: (1) forested area, (0) non-forested area. Broadleaf and coniferous forest stands, and forest massifs were combined in the forested area. Based on the Sentinel-2s spatial resolution, the smallest area where forest cover has been detected is 10 x 10 square meters. Despite this, the size of the smallest mapping unit (MMU) is 0.5 hectares as the image obtained as a result of the classification process has been filtered to eliminate existing gaps and noise. In the end, we obtained 1:30,000 scale forest cover images of 2016 and 2021 whereby forest areas were estimated in the next stages of the project (See Image 5).

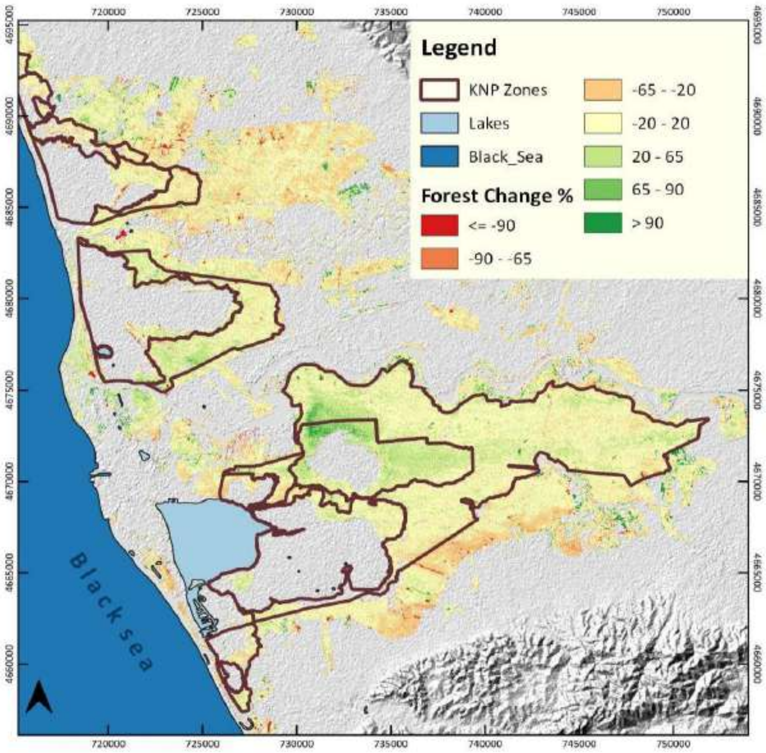
Image 5. Forest cover map (forest/non-forest)

The MAD model with continuous values of tree density change shows change in values, which in our study ranges from -1 to 1 and is expressed in absolute values. The further the value is from 0, the more changes have occurred in the forest. Negative values indicate the degree of deforestation, while positive values indicate forest regeneration or an increase in biomass. Low values are characterized by those places that are under the high anthropogenic influence or were under the high anthropogenic influence during the past years, for example, felling areas, roadside forest stands, places of intense flooding, etc. The degree of change increases where human settlements are located close to the forest or where forest stands are highly fragmented. The image values were later converted to percentages to characterize the changes in the forest canopy better. The MAD model of forest cover change reflects any change that occurs in forest cover; therefore, the map shows not only a net loss of woody biomass* > 90% but also a loss of trees of degraded forest areas 20-90%. Tree biomass can be an individual or group of trees occupying a given area unit (Briggs 1994).

Based on the obtained model, seven conditional categories of changes in tree biomass were identified in the pilot area covered with forest:

1. Loss of tree biomass >90%
2. Loss of tree biomass > 65-90%
3. Loss of tree biomass > 20-65%
4. No change (slight increase or decrease in trees)
5. Increase in tree biomass > 20-65%
6. Increase in tree biomass > 65-90%
7. Increase in tree biomass > 90%

According to this, it is possible to discuss the processes of forest restoration or degradation, because forest areas where the loss of tree biomass is more than 90% can be considered deforested, and those areas of the forest where the total biomass of trees decreases from 20 to 65%, can be conditionally considered as degradation.



Picture 6. MAD change model and borders of Kolkheti National Park. Red pixels show tree loss, while green pixels show an increase in tree biomass.

As a result, we got a map showing the percentage ratio of decrease or increase in trees in the forest cover. The map can be used to assess anthropogenic activities and natural processes in the forest part of the pilot area (see map 6).

Table 2. The percentage ratio of tree biomass decrease and increase in different forest categories.

Forest Categories	Area of Forest Categories (ha)	Forest Change Class	Percentage of Change %
Strict Protection Zone	12753.3	Tree biomass loss >90	0.2
		Tree biomass loss 65-90%	0.1
		Tree biomass loss 20-65%	1.6
		No change	14.3
		Increase in tree biomass 20-65%	13.2
		Increase in tree biomass 65-90%	1.2
		Increase in tree biomass >90	0.2
Managed Protection Zone	674.4	Tree biomass loss 65-90%	0.1
		Tree biomass loss 20-65%	12.6
		No change	28.9
		Increase in tree biomass 20-65%	7.9
		Increase in tree biomass 65-90%	0.2
		Increase in tree biomass >90	0.0
Traditional Use Zone	13659.7	Tree biomass loss >90	0.1
		Tree biomass loss 65-90%	0.1
		Tree biomass loss 20-65%	7.3
		No change	61.4
		Increase in tree biomass 20-65%	22.5
		Increase in tree biomass 65-90%	0.7
		Increase in tree biomass >90	0.2
Commercial Forest	22200.1	Tree biomass loss >90	1.2
		Tree biomass loss 65-90%	0.7
		Tree biomass loss 20-65%	29.2
		No change	52.1
		Increase in tree biomass 20-65%	14.0
		Increase in tree biomass 65-90%	0.7
		Increase in tree biomass >90	2.2

Discussion

In this study, we identified areas of degradation and deforestation of the Kolkheti Lowland forests which were calculated using the Multivariate Alteration Detector (MAD) algorithm. The model clearly shows the dynamics of the processes taking place in the forest in recent years. High model values show the possibility of determining the complete reduction or increase in the forest area which is a sign of deforestation. Medium and low values indicate structural changes in forest cover in a particular time interval, which indicates forest degradation, restoration, or other ecological processes. To establish forest changes, both spectral and spatial resolution were found to be sufficient to create models which is also proved by field trials and comparison with very high-resolution satellite imagery.

It should be noted that other types of models, such as the leaf area index LAI and NDVI, were also tested to estimate deforestation and degradation, but due to the complex structure of forests in the study area and the multi-layered vegetation, the use of LAI was not possible. For example, when comparing models, in a number of felling areas, the LAI values increased instead of decreasing because only the trees forming the upper layer were cut in the forest and the undergrowth remained unchanged. It should be noted that the vegetation of the lower forest layer was characterized by higher LAI and NDVI values than the trees and plants of the upper forest layer, which caused errors in the results. To solve the problem, more complex algorithms were used that take into account images composed of spectral channels in the calculations. As a result, using the MAD algorithm, the change was determined only in the upper layer of the forest cover. In this process, the B11 Sentinel-2 spectral channel turned out to be especially important, since with the help of this variable, it became possible to separate the vegetation of different layers from each other.

The model clearly shows areas of deforestation and degradation, which are present in almost the entire zone of the study area. The scale of deforestation in this time interval is quite small compared to the total area of Kolkheti forests which indicates the specifics of anthropogenic activities. During the last 6 years, large-scale clear-cutting has not been carried out in the forest, which possibly indicates a low commercial interest of the population toward timber extraction. Unfortunately, the opposite appears with respect to forest degradation the scale of which covers almost the entire territory and is especially noticeable near settlements and unprotected areas. The degradation is especially noticeable in the forest area between Munchia and Khobistskali rivers. According to our model, the state of the forest is also affected by the presence of a protected area - the Kolkheti National Park. The forest located within its boundaries is healthier. Apart from deforestation and degradation, there is also a process of forest regeneration which is observed mainly in the territory of the Kolkheti National Park and probably should be associated with changes in the hydrological regime and climate, since an increase in tree biomass is observed in places where the forest was previously heavily flooded, however, now the intensity of flooding may be decreased.

Our model is much more sensitive toward the changes in forests than the GFW model (Hansen et al. 2013). 715 hectares of deforestation were identified, when there is practically no deforestation on the GFW map in the specified time interval. Another forest degradation model that was created based on a 32-year Landsat serial analysis for the territory of Georgia should also be noted (Chen et al. 202) however, the results could not be compared as the study material was not available. It should be noted that, in addition to the above studies, the dynamics of the forest of the pilot area were not evaluated. Therefore, our study is the first within the framework in which it became possible to determine the change of the forest cover quantitatively. Thus, at this stage, the modeling methodology (Annex 1 Flowchart of work) is applicable only to lowland areas. However, we think that in the future it will be possible to create a universal model that will work for mountainous areas where the forest vegetation is different, and the slopes are steep and rugged.

Findings and recommendations

Based on Sentinel-2 multispectral satellite images, maps of forest loss and degradation were created on the Kolkheti lowland, in particular, on the territory of the Kolkheti wetland forests. The results showed that forest change is mainly associated with human activities and is quite intense in areas where forest protection is not carried out by the Agency of Protected Areas. Forest change is more related to forest degradation than to deforestation since the harvesting of timber by the population is mainly carried out through selective cuts. In the study area, not only degradation is observed, but also forest regeneration, which, in our opinion, is related to climate and hydrological regime changes leading to an increase in tree biomass. Various methods were tested to determine changes in the forest, however, depending on the specifics of the forest structure and cuts (felling area), it was best to observe the forest dynamics using a set of spectral channels and a Multivariate Alteration Detection MAD. The model's accuracy was determined by comparison with very high-resolution Maxar images, where forest reduction or growth was visible at the individual tree level. Based on the objectives of the project, no tree biomass in the field was estimated at this stage, for which reason accuracy verification statistically could not be performed. Despite this, for the first time, a change model has been created for the forests of Kolkheti, which can be used by forest management authorities (Administration of Protected Areas, Agency of Protected Areas, National Forestry Agency, Forestry Agency of Adjara, etc.) and environmental organizations for forest/biodiversity monitoring and effective zoning. Considering the methodology and results presented in this study, it is advisable to continue the assessment of biomass and prepare scientific publications, also, to prepare a policy paper for decision-makers and other stakeholders outlining what needs to be done at the policy/legislative level for this study to contribute to biodiversity monitoring and the monitoring results to influence decision-making related to management. The same publication will assess the impact of current forest management practices on the environment/biodiversity.

Kolkheti National Part, Colchic forests, Part of the UNESCO World Heritage

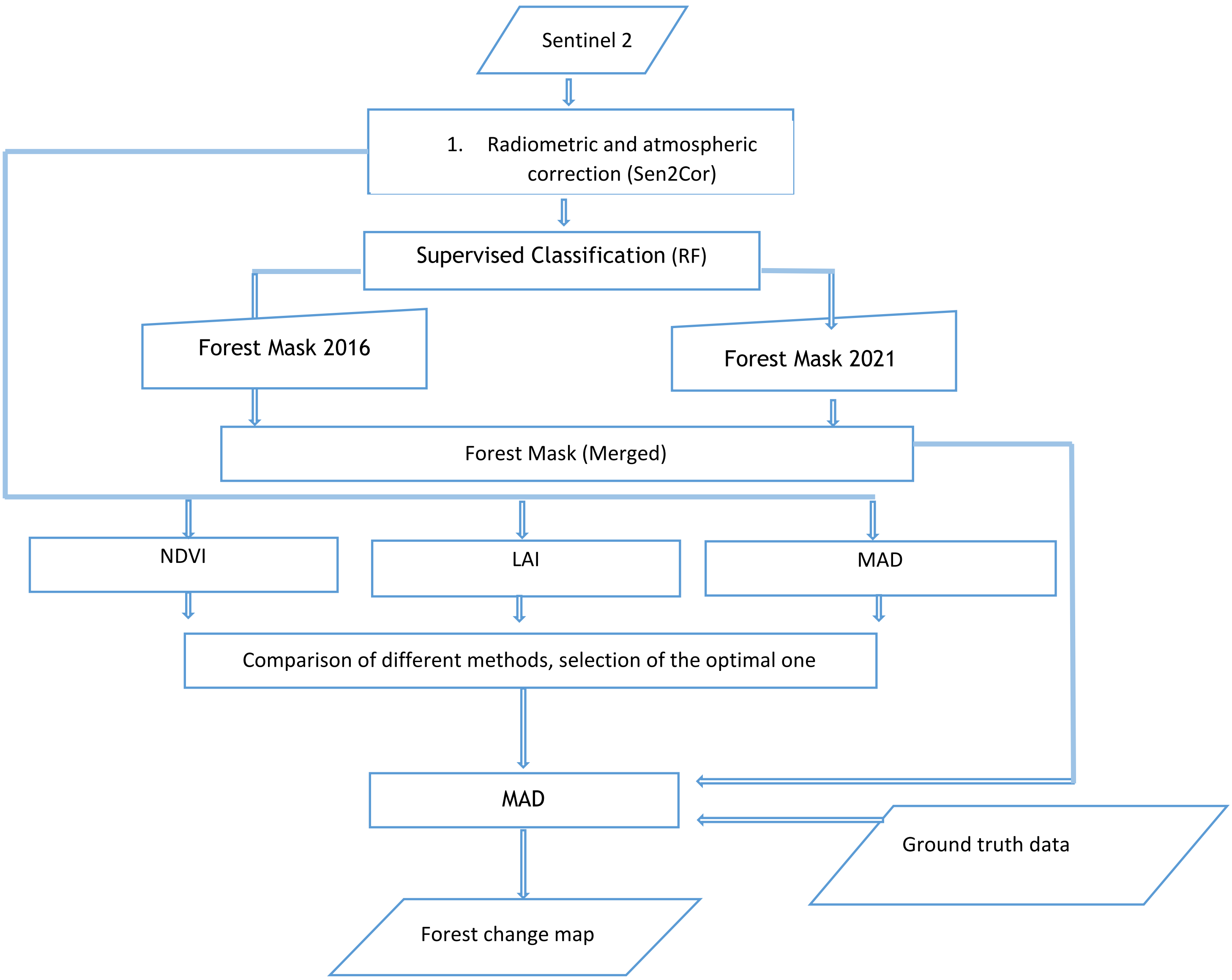
Kolkheti lowland forests, degraded after the clear cuts.

Kolkheti lowland forests, degraded after the clear cuts.

Common alder (*Alnus glutinosa*) grows directly on the swamp.

Artificial stands of maritime pines (*Pinus pinaster*).

Annex 1 (Flowchart of work)



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