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LAND COVER CHANGE DETECTION FOR AMALGAMATED TERRITORIAL COMMUNITIES: EXAMPLE OF USING REMOTE SENSING FOR FOREST CLASSIFICATION AND DEFORESTATION DISCLOSURE

The study is aimed to apply remote sensing for purposes of land cover detection in researches of new territorial units in Ukraine. The example of forest detection using Landsat images is particularly presented in the study. While the study area presented by Korovyntsi amalgamated territorial community in the Sumy region. The forest classification and deforestation detection have been processed for every 5 years from 1990 through 2020.

The Landsat 5, 7, and 8 data from the United States Geological Survey (USGS) have been used for the research. The image choose depended on the date of data availability and reliability, but in time between mid-May to early July. The dataset of 11 total images was processed in the Harris Geospatial Solutions' Environment for Visualizing Images (ENVI). The data were calibrated by using the ENVI Landsat calibration tool, the atmospheric correction applied by using the ENVI FLAASH tool, and seamless mosaicking was used for some periods with more than one images needed.

Normalized Difference Vegetation Index (NDVI) is the basis for forest classification applied. Comparing remote sensing data from different years and different Landsat satellites allowed not just to identify vegetation type of forest, but also to detect land cover changes. The change detection has been analyzed in two ways. The first method was based on changes in classification status. The second method was based on a difference in NDVI values, while forest classification was held for masking out non-forest areas.

The applied study observed ways of cost-efficient land use research for local communities. Those methods could be used by NGO's, local activists, citizen scientists, local authorities for improving land use management with the most updated data, and identifying problems of deforestation, in case of the study presented. Nonetheless, land cover change detection is not limited to forest cover presented in the study. Anyway, in the case of forest detection, Landsat images from different satellites could be compared and present historical data for the rural areas, which had a low research interest in the past, but it changed due to administrative reform in Ukraine and switching governance power to the local communities.

Keywords: remote sensing, land cover change detection, deforestation, rural community.

Introduction. Decentralization reform in Ukraine switched attention in regional planning to local communities, as they became mostly responsible for local governance. The amalgamated territorial communities (ATC, or hromada) were created and were given the power of community planning. Rural communities became an object of planning research related to state-level planning issues, as well as local improvement levels of research-driven not only by the government of Ukraine. Geospatial data is basic and important information for management decisions, especially related to spatial planning and community development. The lack of detailed and rural-communities-oriented datasets requires a search for reliable and efficient sources of the data, so local communities could rely on it in governance and deeply improve the impact of decentralization.

Research Statement and Purpose. The purpose of the project is to determine ways of using free-access remote sensing data for forest management purposes and the needs of local communities in Ukraine on the example of the Korovyntsi rural community, Sumy oblast. Change detection within division boundaries through time, beginning from the Soviet Union collapse through the transition period up to date. The Korovyntsi rural hromada, Sumy region, was selected as a project region. The area is around 250 sq. km (96.5 sq. mi). The community located within the valley of the river Sula, within the upper river basin, and the river splits the community into the south (agricultural) and north (forest) part. The forestation rate for the community is 20%, which is above the average forest cover of the Sumy oblast (17,8%). Coniferous forest (Scots pine, Spruce, and Larch) is dominating in the northern part of the community, while broadleaf and mixed forests (birch, black alder, aspen, basswood, poplar, willow) can be found on both sides and occupy small areas.

Research Questions:

1. How free satellite image data can be used for forest monitoring, as an element of land-use change detection, by local communities?
2. How deforestation analysis can be performed by using remote sensing tools?
3. How deforestation can be detected by using Landsat open data?

Goals

To achieve these goals shall be enacted the following tasks:

- to map forest cover change in the community (1990–2020) from Landsat TM/ETM+ images by using NDVI;
- to compare NDVI from different images and to identify deforestation area within the community;
- to map forest change by using dNDVI;
- to access the spatial pattern of logging based on regeneration for detecting deforestation.

Literature review. Mapping and monitoring of land-use changes of the territory of Ukraine were presented in several studies and published in scientific and professional journals mainly after 2011 due to the increasing of researches based on free data from US and EU remote sensing data sources. Lately, Ukrainian regions were a part of the inter-state studying of the Carpathian region. Western Ukraine became a major study area for researches, because of the variety of land covers: agricultural lands, forests, mining areas, and combining with mountain regions. It allowed producing studies on cropland changes, canopy layers, forest studies, amber removal, snow cover changes, etc. within one region of Ukraine.

Land use differences are the main purpose of remote sensing studies for planning or management purpose. Stefanski, et al. (2014) [8] made a long-range analysis of land-use changes of Western Ukraine from 1986 through 2010 years. Land use patterns were compared to social-economical changes in the country: the collapse of the Soviet Union and the transition to a free-market economy of independent Ukraine. The mapping of cropland, grassland, forest, and urban classes of land use was made for 5 periods of different regimes by referring to 1986, 1993, 1999, 2006, and 2010 years. The study required an adequate data set for one time period and the monitoring of land management changes required multitemporal data sets from different years for the same study site. Stedanski, et al (2014) [8] used the Landsat data for the research, even defined problems regarding the repetition rate of typical systems like Landsat and the problem of cloud cover, where the generation of adequate multitemporal data sets can be challenging. The study also rejected using of other sources for the research purpose which are inadequate in capturing land use and cover changes at fine scales, even there are data with higher temporal coverage and wide swath, such as MODIS and MERIS. The Random Forest classifier (Breiman, 2001) [8] was used for the classification of the images. This study represents classical land use change mapping of major types of land activities.

There were conducted also specific studies on someone type of land activity, but also mainly for the same Wester Ukraine. However, because of the huge social interest in some planning issues in the northern part of Ukraine, there are some study regards detecting illegal land use activities by using remote sensing data. Hnatushenko, et al (2017) [3] presented the study on detecting illegal extraction of amber in Ukraine. Landsat-7 and Landsat-8 datasets were used during the change detection between 2002 and 2015 years. Forest cuts and remained soaked deep pits in the soil became a major detection marker for illegal extraction of raw amber. Principal component analysis of multispectral satellite images, threshold binarization of the differential image, morphological filtering if the binary image, vectorization, and calculation of geometrical characteristics were performed for detecting and visualization of the changes on a map. It allowed us to detect and classify extracting sites into two categories: new and old. Anyway, even this study was not based on forest detection, it defined forest complete cuts without regenerations, and classified areas by new/old activities.

Most of the forest-related studies were made for the Carpathian mountain region. Kuemmerle, et al (2007) [5] researched post-socialist forest disturbance in the Carpathian border region in Western Ukraine. The disturbance index, based on Tasseled cap indices, was used for change analysis of forest within the study area for 1977, 1979, 1988, 1994, and 2000 years. Landsat images from 1986-1988 were used to separate the forest from the non-forest. The study was challenged with imagery from autumn due to mixed class detection of broad-leaved forests and meadows but fixed this problem by using unsupervised iterative self-organizing data analysis. Water pixels were masked out using thresholds for the near and mid-infrared bands. All patches below a threshold of 30 pixels were labeled as non-forest with the purpose to exclude small areas that are functionally not a forest. The 1977 and 1979 imagery were used in the case to determine if forest openings were clear-cuts or permanent opening. The forest/non-forest map was analyzed for presenting all non-forest patches that were within larger forest patches. Based on ground-truth and visual assessment, patches less than 1000 pixels were claimed as forest patches. The disturbance index was calculated for each year and composed image, represented by stacked individual bands into one, was used to identify 'unchanged forest', 'disturbance 2000-1995', 'disturbance 1994–1989', and 'disturbance before 1988'. Anyway, that study did not answer the question of the regeneration of forests or the nature of disturbances.

During the following years, the study by Kuemmerle, et al (2009) [4] presented not just forest cover change, but also illegal logging in the Ukrainian Carpathians in the transition period from 1988 to 2007. Forest cover change mapping was conducted by using support vector machines based on fitting a separating linear hyperplane between two classes in the multidimensional feature space. The Support vector machines were used to delineate forest/non-forest maps for each of the four periods and assessed forest cover changes via post-classification map comparison, by using the software image SVM. All of the maps were mosaicked for further deriving of a forest change map. Additional to time-period classification of disturbance or post-disturbance regeneration, the research defined level (complete or near-complete removal) and type (by anthropogenic processes or natural events) of forest cover changes. The threshold of 7 pixels was chosen for determining non-forest trees because the smallest forest management unit in Ukraine is 0,5 ha. Misclassifications issues in the study also were related to large non-forest areas surrounded by forest above the timberline and narrow disturbances along rivers, which were assigned as permanent non-forest. In addition to classical accuracy assessment of the individual classifications, the researchers conducted a validation of the detectability of disturbances. In the case of the research, difficult methods of classification and change detection were used due to the complexity and scale of the study area.

Another approach of change detection in forests was presented by Mancino, et al (2014) [6] that used NDVI differencing to detect vegetation change for assessing natural forest expansion in southern Italy. Firstly, NDVI was calculated for each image by the general normalized difference between band 4 (near-infrared) and band 3 (visible red) from Landsat TM pre-processed images. The resulting images were subtracted to assess the dNDVI with positive and negative changes. The dNDVI image was also tested to determine fit to a normal distribution. The difference image dNDVI was reclassified using a threshold value for identifying three ranges in the normal distribution. This study considered only the positive variation in forest cover defined as the area of probable natural forest expansion, but it can be used for all three categories detected by dNDVI.

Methodology. The most efficient, in case of availability and cost-efficiency, source of remote sensing data for the project was to use USGS Landsat imagery. For the research time frames of 1990–2020 is best to use Landsat 5 TM from 1989 through 2011, and Landsat 8 OLI from 2013 through 2020. The month of June is the most appropriate due to strong vegetation in forest and still not high vegetation of crops, which can help better separate each from others.

There were two images from Landsat 5 that contains the study area: path 179/ row 25 (full extend); and path 180/ row 24 (partly, without very south small part of the community). Both images can be used, as the forest zone detected only within the northern part of the community and there are only agricultural lands within that excluded part of the second image. There are from 2 to 3 images available for June each year, and only 2 images per year with cloud cover less than 10 %. Depends on the year, image from late May (after 20 th of May) and early July (before 10th of July) can be used as a third image.

There are three images from Landsat 8 that contains the study area (Fig. 2): path 180/ row 24; path 179/ row 25; and path 180/ raw 25 (not valid for 2013). There are from 5 to 6 images available for June each year, and only 2 images per year with cloud cover less than 10 %. Cloud cover will be evaluated for both Landsat 4 and 8 during data collection and decided if some additional images from May or July are needed due to the level of cloud cover of the study area.

The following periods were chosen as the period for time analysis of forest change within the region: 1990, 1995, 2000, 2005, 2010, 2015, and 2020. The Landsat 5, 7, and 8 has been chosen for data sources in this project, instead of proposed previously only two of them – Landsat 4 and Landsat 8. Such a decision has been made after exploring the images from Landsat 5 for periods of 2000, 2005, and 2010. June was projected the main month of a year for the images with the possibility to take reliable data from May 25th through July 5th. After exploring data quality for the whole period of 2000 was determined that there are no data for the study area with cloud cover lower than 83 % within Landsat 5 datasets. After looking for Landsat 5 datasets for the same period in 2005 and 2010, it has been observed a high cloud cover level for the study area: more than 40 % scene cloud cover with a high density of clouds in the study area. Using Landsat 7 images for those periods of 2000, 2005, and 2010 is the most efficient way to solve the problem of the image's quality, due to the low cloud cover level.

Change detection in land use during the analysis period has been analyzed using the NDVI differencing technique. First, NDVI was calculated following the general normalized difference between near-infrared (B4) NIR and visible red band (B3) Red from Landsat 5/7 images and between near-infrared (B5) and visible red band (B4) from Landsat 5/7 images:

$$NDVI = NIR – Red / NIR + Red$$

NDVI results have been used for mapping forest (values between 0,7–0,87 depends on the year and type of sensors used). Two ways of determining changes have been used during the project. Firstly, two different period forest maps have been compared due to detecting new forested areas and harvested areas, as a difference between two pixels of forest and non-forest value. Secondly, the difference between NDVI from two years helped to determine forest change: dNDVI = NDVI (1995) – NDVI (1990), etc. During combining few dNDVI we would be able to see continuous patterns in foresting: negative dNDVI determines deforestation, positive dNDVI – regenerating process, and continuous negative dNDVI values – inefficient forest harvesting.

Preprocessing. The study area located within three possible image positions in used Landsat datasets: 1) path 179 row 25; 2) path 180 row 24; and 3) path 180 row 25. The study area is fully presented within path 179 row 25 on each of the datasets, as well as also fully presented within path 180 row 24 on Landsat 8 dataset. In the same time, path 180 row 25 covering the northern part of the study area for each dataset, and path 180 row 24 covering the southern part of the study area for Landsat 5 and Landsat 7; but none of them covering the south-east part of the study area, which is fully covered by agricultural lands. Several images from one time period have been used due to the low quality of basic image path/row: 1) path 180 row 24 is a basic image with the south part, 2) path 180 row 25 is an additional image with the northern part, and 3) low qualitative path 179 row 25 is the additional image with the south-east part.

For instance, the dataset of 3 images for 1990 has been chosen because of the high cloud level within the exact study area, and a low-quality image from path 179 row 25 has been used as additional because path 180 did not cover the south-east part of the study area. Different reasons for using path 179 row 25 image as third presented in the 2005 dataset, because there are images from path 180 with good quality dated within the planned time frames, but they are not covering the south-east part. That gup has been filled by adding an image from path 179 row 25 dated by May 22nd, as that area is not covered by forest and would not make a big impact on classification.

Twelve Landsat 5, 7, and 8 images have been used for the project because of exploring the datasets and determining reliable data for the analysis during each period needed for the research. All the images have a 30-meter resolution for near-infrared and red bands, which is needed for the project NDVI calculations. The project data has been downloaded from the USGS (see tab. 1).

***Table* 1. Datasets inventory**

Year/period	Satellite	Date	Path	Row	Cloud cover	Filename [downloaded from 9]
1990	Landsat 5	22-JUN-90	179	25	16	LT05_L1TP_179025_19900622_20170130_01_T1
		29-JUN-90	180	24	2	LT05_L1TP_180024_19900629_20170130_01_T1
				25	1	LT05_L1TP_180025_19900629_20170129_01_T1
1995		04-JUN-95	179	25	2	LT05_L1TP_179025_19950604_20170109_01_T1
2000	Landsat 7	25-JUN-00	179	25	9	LE07_L1TP_179025_20000625_20170211_01_T1
2005		22-MAY-05	179	25	1	LE07_L1TP_179025_20050522_20170114_01_T1
		29-MAY-05	180	24	0	LE07_L1TP_180024_20050529_20170114_01_T1
				25	0	LE07_L1TP_180025_20050529_20170115_01_T1
2010	Landsat 5	13-JUN-10	179	25	0	LT05_L1TP_179025_20100613_20161015_01_T1
2015	Landsat 8	02-JUN-15	180	24	18.36	LC08_L1TP_180024_20150602_20170408_01_T1
2020		06-JUN-20	179	25	10.25	LC08_L1TP_179025_20200608_20200625_01_T1

First of all, all distributed *.tiff images with band's data using the metadata information has been calibrated to radiance data by using the ENVI Landsat calibration tool and then stacked together. Layer Staking has been processed after that for each dataset with the following parameters: datum WGS84, UTM zone 36 N, 30 x 30 pixel, nearest neighbor resampling method. All 6 Multi-spectral bands for Landsat 5, Landsat 7, and Landsat 8 have been processed in the ENVI.

Secondly, atmospheric correction using the ENVI FLAASH has been made for all stacked images. BIL files, converted from BSQ stacked previously images, have been used for the FLAASH tool. The correction has been made with the image's flight date and time from metadata, elevation, latitude, and longitude of the center of the scene of each image and the following parameters: 10 scale factor, 30 x 30 m pixel size, Mid-Latitude Summer, Rural atmospheric model, 2-Band (K-T) for each Landsat type.

Thirdly, Seamless Mosaicking used for combining images for 1990 (3 images), and 2005 (3 images). After that, the raster files were clipped in ENVI by shapefile of the study area and transformed into WGS84 UTM 36 N.

Data analysis. NDVI has been calculated for each period images by using Near Infrared and Red bands:

Band 4 and Band 3 for Landsat 5\7, and Band 5 and Band 4 for Landsat 8. NDVI, calculated for Landsat 8, has been multiplied on the value of the correlation coefficient – 0.906 (Roy et al., 2016) [7]. Forest fractions were determined by NDVI low (V1) and high (V2) values as following: 0.79 – 0.87 for Landsat 5 TM, 0.71 – 0.86 for Landsat 7 ETM, and 0.79 – 0.86 for Landsat 8 OLI.

Based on NDVI images, classification by using decision tree has been processed: all values higher than V1, and then lower than V2 has been classified as a forest with value 1; all values out of that range have been classified as non-forest with value 0. There is some difference between V1 and V2 values for different Landsat images, based on detected areas. The value of V2 has been decreased for 0.01 for Landsat 7 and Landsat 8 images because it helped to exclude big areas of crops. The value for V1 has been decreased for 0.08 for Landsat 7 because it allowed detecting forest areas from previous years. There is some difference between Landsat 5 and Landsat 7 NDVI values, not just because the visual result of applied V1=0.79 was highly different from previous periods, but also, because of the difference in NDVI mean values for Landsat 7 images which is lower on 0.10 – 0.11 compared to Landsat 5 images.

Classification of the forest areas with described previously NDVI values also detected some crop fields with NDV values of 0.81 – 0.84 for Landsat 5 and Landsat 8, and 0.78 – 0.81 for Landsat 7 images. The suggestion, that images from the early Spring can be used better than June's images, has been tested using an image from April 3rd, 1990 (LT05_L1TP_179025_19900403_20180218_01_T1). The test comparing two classifications of images from June and April showed that there are no significant differences, moreover, image from April with lower NDVI values for the forest, also can cover more areas of crop fields. There are was also a suggestion of using winter images for forest detection, but all images from January to April for the study area have a cloud cover of 100%. Nonetheless, images with snow cover will not allow detecting broadleaf forests in the southern part of the study area, which is mainly represented by windbreak forest and fruit gardens. Moreover, the snow cover is usually gone at the end of March – beginning of April for those areas. At the same time, both classifications, June and April images, were visually good for detecting coniferous forest in the northern part of the study area. That is why masking out crop fields has been chosen as a method of excluding crops from forest classification. Mask shapefile has been created by overlying classification raster with Google imagery and making crop polygons for those areas, which are visually within crop fields. Such overlay has been made for each period image and all polygons have been combined. The combined mask shapefile has been used for masking out areas with value 1 and changing them to value 0 in classification raster.

The first method of detecting deforestation processes is based on comparing two periods of classification maps. Band math (B2-B1) has been used for creating a new image with 3 classes: "no changes", "reforestation", "deforestation". Because each classification has 0 and 1 values, we expected to have 3 different results after operation of deducting from the newest image older: -1 – deforestation; 0 – no changes; +1 – reforestation.

Because, the previous method is just comparing classification outputs and taking into account only pixels' values created through classification, the second method of detecting deforestation processes has been applied. Changes in NDVI values can show a rapid and high decline in NDVI value for each analyzed pixel. First of all, the dNDVI images have been created for each period: dNDVI(1995)=NDVI(1995)-NDVI(1990), etc. Because all values of NDVI are between 0 and 1, all output dNDVI values can be in the range between -1 and +1.

During the next step, a decision tree has been used for the classification of dNDVI, as the second method of deforestation detection. Because of the previous appearance of -1 value, this time we looked to values lower than -0.2, which would mean that NDVI has been decreased a lot between two comparable years. All dNDVI lower than -0.2 got a value of 5, and all dNDVI higher than 0.2 got a value of 3. Because, the dNDVI also covering all crops in the study area and all values with change lower than -0.2 also can be a decrease of NDVI value in crops, forest classification for the newest year has been taken as a base map of forest areas. For detecting cuts within the forest areas we deducted forest classification (Forest) with 0 or 1 values from dNDVI changes classification: Deforestation(1995)=dNDVI_1995vs1990-Forest(1995) etc. As a result, the new values were obtained: 2 – no changes within a forest, 3 – no changes outside forest areas, 4 – a decline of NDVI outside forest areas, and 5 – deforestation.

Accuracy assessment. Classified forest images have been assessed by using generated random samples and compared with images from Google Earth Pro time-series. The total sample size was chosen as proportional to 0.025 %, which is 117 pixels: 10 pixels with forest, and 107 with non-forest. The method of determining producer and user accuracy has been applied. The overall accuracy for the dataset is 94–95 % for Landsat 7, 95–97 % for Landas 8, and 98–99 % for Landsat 5 images. Classified deforestation areas have been assessed by using generated random samples and compared with images from Google Earth Pro time-series. The total sample size was chosen as disproportional 100 pixels: 50 pixels with cuts, and 50 pixels without cuts. The assessment has shown that there are no shreds of evidence when non-cuts areas were classified as cuts, but there are 10–17 % of cuts pixels, which are non-harvested areas. The overall accuracy for dNDVI based classification is in the range of 90–97 % depends on the images compared.

Results and Discussion. According to forest classification, there is a trend on increasing forest cover within the study area from 1990 through 2020 (fig. 1), with two peaks in 1995 and 2015: from the lower 16.15 % to 23.15 %, which is within typical for East European forest-steppe ecoregion range of 10-25 %. Moreover, the forest cover of the study area was higher than the country average 15,9 % [2] throughout the whole period from 1990 to 2020 and was lower than the regional average only in 2000 and 2005. Based on the analyses performed, the forest shares compared to the territory of the study area can be presented as follows: 1990 – 17.76 %, 1995 – 21.65 %, 2000 – 16.15 %, 2005 – 17.22 %, 2010 – 18.7 %, 2015 – 23.15 %, 2020 – 20.22 %.

Detecting deforestation via forest classification change provided comparing only classification differences, and show that all harvesting values are overrated. Anyway, that method is also allowed to define reforestation areas, which are higher than in harvested areas. The highest level of deforestation also was detected for 2000 vs. 1995 period by using this method. This period is represented by the economical decline in the country, as well as the decline in the timber industry.

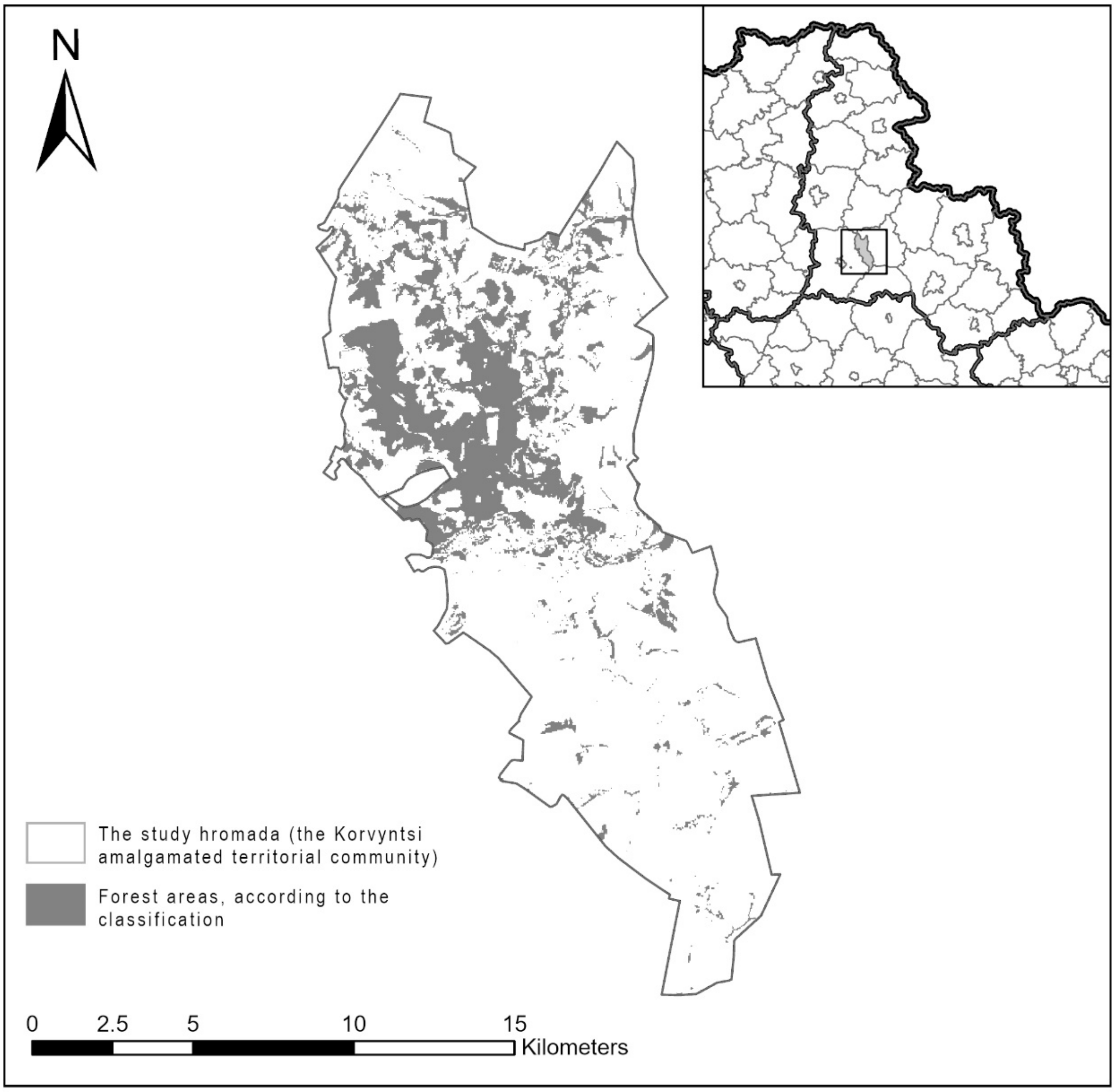

Fig.1. Forest classification for the 2020 year

Detecting cuts via a change in NDVI provided more reliable results. The deforestation rate is under 1.3 % range of cuts during the whole period, except 2000–2005 when it was about 3 %, while the previous 2000–1995 period has zero range of harvesting. It can be explained by the economic decline during 1995–2000 and economic boom after 2000 when the timber industry also increased production. This method also shows an increase in harvesting after 2015. Nonetheless, there are some missed values of forest areas, if the deforestation areas and areas with no change in a forest can be counted for calculation next period forest cover. It might be due to a loss in dNDVI values between 0 and -0.2.

Detected cuts polygons by using the second method, also allowed to visualize those areas. Mostly, harvested areas are located within the coniferous forest zone on the north of the study area, and those areas are designated for harvesting and foresting in cycles. There are also some cuts within the south of the study area and mostly related to harvesting old windbreak forests due to power lines and gas pipelines, or to private decisions on private gardens.

The differences in forest cover share in land can tell that there is some missed forest due to the classification method, or both missed forest and captured crops. Using mapped all crop fields, as a mask, can be a solution for excluding that land use type from the classification because they have the same range of NDVI as a forest. Moreover, comparing early April and June data shown that there are still can be areas with the same NDVI values as forest. Because, crop fields are immutable, making one shapefile based on 10-m Google images from 2020 can be a real and useful solution for future research.

Accuracy assessment also could be improved. Currently, due to the low share of forest vs. Non-forest areas and cuts vs. Non-harvested areas, using 100 pixels for forest and cuts will result in 1086 pixels of non-forest class, and 33016 pixels of non-harvested areas.

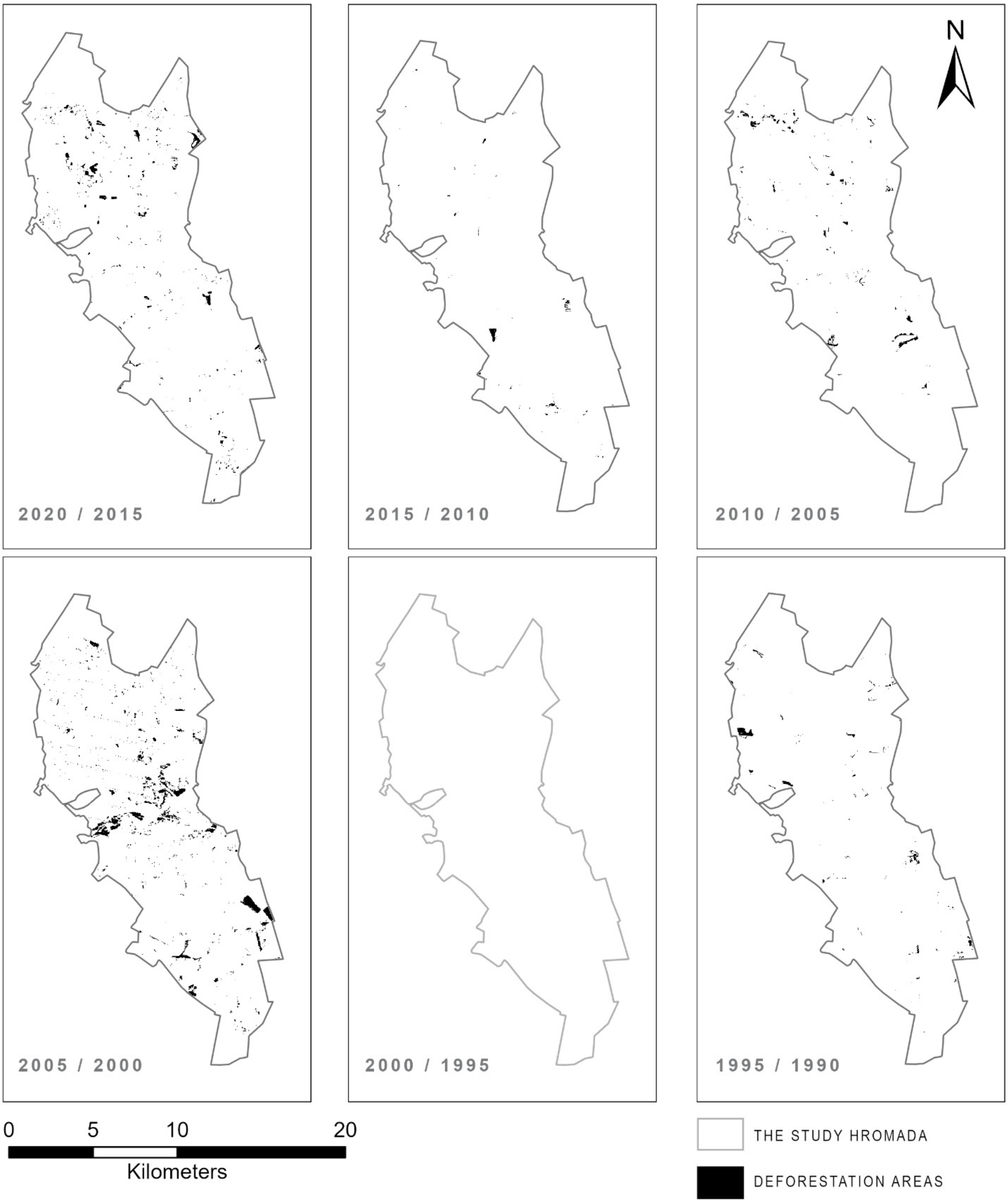

Fig. 2. Detecting deforestation areas based on dNDVI classification

Remote sensing can and must be used by local authorities, activists, citizen scientists, NGO's, etc., especially in case of improving local governance. The latest valuable data could be urgently obtained and processed for decision making. The forest detection is only one example for land cover change detection and determining land-use patterns. Open data from the USGS and Landsat data has a high resolution of 30x30 meters in case of using red and near-infrared, so there are a lot of possibilities for applied studies on land cover detection. The long history of satellite operating by the Landsat program provides data for historical analysis with minimal losses in data correction for different types of sensors. Moreover, such analysis might be processed via free tools of Google EarthEngine with similar results. The study could conclude a huge potential of remote sensing for usage in regional, urban, rural, and community planning purposes.

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ВИЗНАЧЕННЯ ЗМІН ЗЕМЛЕКОРИСТУВАННЯ В КОНТЕКСТІ ОБ'ЄДНАНИХ ТЕРИТОРІАЛЬНИХ ГРОМАД: ПРИКЛАД ВИКОРИСТАННЯ ВІДДАЛЕНОГО СПОСТЕРЕЖЕННЯ ДЛЯ ВИЗНАЧЕННЯ ЛІСИСТОСТІ ТЕРИТОРІЇ ТА ЇЇ ЗМІН

Дослідження спрямоване на застосування методів віддаленого спостереження з метою виявлення змін у землекористуванні при дослідженнях громад – нових територіальних одиниць в Україні. Застосовано приклад виявлення та класифікації лісів за допомогою зображень супутників Landsat. Досліджуваний район представлений межами Коровинської сільської об'єднаної територіальної громади Сумської області. Класифікація лісів і виявлення вирубки лісів проводилася за даними знімків періодами п'ять років із 1990 по 2020 р.

Для дослідження використовувались дані Landsat 5, 7 та 8 Геологічної служби США (USGS). Кількість і дата використаних знімків залежали від їхньої якості, але в основному датуються другою половиною травня – початком липня відповідних років. Набір із 11 загальних знімків оброблено в середовищі для візуалізації супутникових знімків Harris Geospatial Solutions (ENVI). Дані були відкалібровані за допомогою інструменту калібрування ENVI Landsat. Атмосферну корекцію застосовано за допомогою інструмента ENVI FLAASH; безшовне мозаїчне зображення використовувалося протягом деяких періодів із кількома необхідними знімками.

Нормалізований диференційний вегетаційний індекс (NDVI) є основою для класифікації лісистості. Порівняння даних віддаленого спостереження різних років та різних супутників Landsat дозволило не лише визначити рослинний тип лісу, а й виявити зміни земельного покриву. Виявлення змін було проаналізовано двома способами. Перший метод базувався на зміні статусу класифікації, другий – на різниці значень NDVI, тоді як класифікація лісів застосовувалася для маскування нелісових територій.

У цьому прикладному дослідженні було застосовано шляхи економічно ефективних досліджень використання земель для місцевих громад. Ці методи можуть бути використані неурядовими організаціями, місцевими активістами, цивільними науковцями, місцевими органами влади для вдосконалення управління землекористування з використанням найсвіжіших даних та виявлення проблем лісів. Тим не менше, виявлення зміни земельного покриву не обмежується лише лісовим покривом, представленим у дослідженні. У випадку класифікування лісистості, зображення Landsat із різних супутників можна порівнювати та представити історичні дані для сільських районів, які в минулому становили низький науковий інтерес, але наразі інтерес до них зріс унаслідок адміністративної реформи в Україні та переходу управлінських рішень на місцевий рівень.

Ключові слова: віддалене спостереження, дистанційне зондування, зміни землекористування, лісистість, сільська громада.

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ОПРЕДЕЛЕНИЕ ИЗМЕНЕНИЙ ЗЕМЛЕПОЛЬЗОВАНИЯ В КОНТЕКСТЕ ОБЪЕДИНЕННЫХ ТЕРРИТОРИАЛЬНЫХ ОБЩИН: ПРИМЕР ИСПОЛЬЗОВАНИЯ ДЗЗ ДЛЯ ОПРЕДЕЛЕНИЯ ЛЕСИСТОСТИ ТЕРРИТОРИИ И ЕЕ ИЗМЕНЕНИЙ

Исследование направлено на применение методов ДЗЗ с целью выявления изменений в землепользовании при исследованиях общин – новых территориальных единиц в Украине. Применен пример выявления и классификации лесов с помощью изображений спутников Landsat. Регион исследования представлен Коровинской сельской объединенной территориальной общиной Сумской области. Классификация лесов и выявления вырубки лесов проводилась по данным снимков периодами в 5 лет с 1990 по 2020 г.

Для исследования использовались данные Landsat 5, 7 и 8 Геологической службы США (USGS). Количество и дата использованных снимков зависели от их качества, но в основном датируются второй половиной мая – начала июля соответствующих лет. Набор из 11-ти общих снимков обработано в среде для визуализации спутниковых снимков Harris Geospatial Solutions (ENVI). Данные были откалиброваны с помощью инструмента калибровки ENVI Landsat. Атмосферная коррекция применялась с помощью инструмента ENVI FLAASH; бесшовное мозаичное изображение использовалось для некоторых периодов с несколькими необходимыми снимками.

Нормализованный дифференциальный вегетационный индекс (NDVI) является основой для классификации лесов. Сравнение данных ДЗЗ разных лет и разных спутников Landsat позволило не только определить растительный тип леса, но и выявить изменения земельного покрова. Выявление изменений были проанализированы двумя способами. Первый базировался на изменении статуса классификации, второй – на разнице значений NDVI, тогда как классификация лесов применялась для маскировки нелесных территорий.

В этом прикладном исследовании использовались пути экономически эффективных исследований изменения землепользования для местных общин. Эти методы могут быть использованы неправительственными организациями, местными активистами, гражданскими учеными, местными органами власти по совершенствованию управления землепользованием с использованием самых свежих данных и выявления проблем лесов. Тем не менее, выявление изменения земельного покрова не ограничивается лесным покровом, представленным в исследовании. В случае классификации лесистости, изображения Landsat с разных спутников можно сравнивать и представить исторические данные для сельских районов, которые в прошлом имели низкий научный интерес, но пока интерес к ним возрос в результате административной реформы в Украине и перехода управленческих решений на местный уровень.

Ключевые слова: дистанционное зондирование, изменения землепользования, лесистость, сельская община.