Landcover Mapping of Floodplains along the Naryn River, Kyrgyzstan Based on Sentinel-2

Chymyrov, A.,[1] Betz, F.,[2] Baibagyshov, E.,[3] Kurban, A.,[4] Cyffka, B.[5] and Halik, U.[6]
[1]Kyrgyz State University of Construction, Transport and Architecture, Department of Geodesy and Geoinformatics, Kyrgyzstan, E-mail: akylbek2005@yahoo.com
[2]Catholic University Eichstaett-Ingolstadt, Faculty of Mathematics and Geography, Germany
E-mail: florian.betz@ku.de,[2] bernd.cyffka@ku-eichstaett.de,[5] uemuet.halik@ku-eichstaett.de[6]
[3]Naryn State University, Department of Ecology, Kyrgyzstan, E-mail: nsu0896@yahoo.de
[4]Xinjiang Institute of Ecology & Geography, Chinese Academy of Sciences, China
E-mail: alishir@ms.xjb.ac.cn

Abstract
The article presents the results of studies on the use of Sentinel-2 satellite data and the application of SNAP and ArcGIS software for the classification and mapping of forest cover of the Naryn river floodplain. Available inventory maps of the Kyrgyz Forestry Administration are outdated and do not meet current requirements and need to be updated with the use of satellite images from different systems. High resolution Sentinel-2A multispectral imagery has been used to study the supervised forest cover classification of the floodplain areas of the Naryn River in Kyrgyzstan for contributing to forest inventory and general analysis of the floodplain forest ecosystems. Using such high resolution images in this study was due to the peculiar properties of classification and mapping of small vegetation areas of the unstable floodplains of mountain rivers. Supervised classification was performed using S2A MSI and World View 2 satellite images through SNAP software and field investigation data. Level-1C S2A multispectral images are processed to the Level-2A using Sen2Cor for the atmospheric corrections and further classification. The research results show the usefulness of high resolution Sentinel-2 imagery for land use and land cover classification as well as the best freely available tool for thematic mapping of riparian forests.

1. Introduction

In the semi-arid climate of Kyrgyzstan, the rivers and their floodplains have a high ecological importance, for biodiversity as well as for the supply of people with relevant ecosystem services (Karthe et al., 2015). For instance, riparian vegetation along the Naryn River provides timber, harvestable fruits or pastoral land. Furthermore, they are an important for mitigating erosion or – from a global perspective – for the climate system via storage of carbon (Betz et al., 2015). Despite the importance of these ecosystems, there is no modern monitoring. Available information is outdated and does not meet the requirements of a modern, effective forest inventory. For instance, there are no recent maps of the forest coverage (Betz et al., 2016). The need for monitoring the floodplain forests along a more than 250 km long stretch of the Naryn River together with a lack of infrastructure in the Naryn catchment makes remote sensing (RS) the method of choice for assessing the state and dynamics of riparian areas along the Naryn River. Over the past decades, a wide range of algorithms has been developed for the processing of remotely sensed imagery and landcover classification (Gomez et al., 2016 and Vorobyev et al., 2015). There are a number of satellite systems, such as Landsat, ALOS, SPOT, which provide low, medium and high resolution images suitable for mapping and monitoring of the forested large areas. Improvements have been made in the assessment of riparian zones from satellite remote sensing. For the European Union, Clerici et al., (2013) presented a continent-scale delineation of floodplain vegetation combining digital terrain analysis with remote sensing and existing data sets. In a similar approach, Betz et al., (2016) estimated the extent and spatial distribution of riparian ecosystems along the Naryn River and its major tributaries. Despite the interesting insights of this Landsat based assessment, the medium resolution of 30 m did only allow distinguishing between vegetation, non-vegetation and water as the Naryn River shows partly narrow floodplain sections.

Use of the very high resolution WorldView-2 image in land use/land cover (LULC) classification is investigated for mapping of the part of study area (Chymyrov et al., 2016). This research has developed

ISSN 1686-6576 /

large scale and high quality thematic maps (1:1000-1:10000) for the forest management unit and ecosystem service management project EcoCAR (Ecosystem Assessment and Capacity Building for sustainable Management of Floodplains along the Central Asian Rivers Tarim and Naryn. But the extremely high cost of such satellite imagery limits their wider use in forest mapping in conditions of Kyrgyzstan.

For management issues, however, information about the exact landcover classes are required. Since 2015, the Sentinel satellites of the European Space Agency (ESA) offer a new remote sensing tool for environmental monitoring (Drusch et al., 2012). The sensors of this satellite offer a wide range of spectral bands with spatial resolutions between 10 and 60 m suitable for manifold tasks of land observations (Drusch et al., 2012). Especially the 10 m resolution in the visible and near infrared make Sentinel-2 imagery an interesting dataset for monitoring small landscape features such as forest patches or Narrow River channels (Radoux et al., 2016 and Ozdogan and Kurban, 2012). The available resolution has a high potential for thematic mapping of floodplain areas with a suitable degree of detail to support research and management of ecosystem services along the Naryn River.

The goal of this study is to create a landcover mapping system of the floodplain areas along the Naryn River using Sentinel-2 imagery. This up-to-date landcover information is the objective basis for further research on ecosystem services of the floodplain forests and can be used as baseline data for future landcover change analysis.

2. Material and Methods

2.1 Study Area

The Naryn River originates in the inner Tian Shan Mountains and flows westwards across Kyrgyzstan towards the arid Fergana valley. The major share of this 807 km long stream is in a near natural state without dams or extensive embankments. There is a number of hydropower stations located in the river basin including the largest Toktogul Reservoir with 19.5 cubic km capacity. The river catchment upstream from the Toktogul Reservoir has a size of 52.130 km². The discharge regime is glacial to nival-glacial with one single peak in July. Climate is highly continental with a high temperature amplitude between summer and winter as well as in generally low annual precipitation of 300 mm (Betz et al., 2016). Riparian areas are mainly composed by Salicaceae like Salix spp. and Populus spp. Further frequently occurring species are Tamarix spp. and Hippophae rhamnoides. The relevant ecosystem services belong to the category of provisioning services according to the classification of the Millennium Ecosystem Assessment (MA, 2005). People get fuel and construction wood or collect the berries of the sallow thorn. Furthermore, the floodplain forests are important pastoral land and are used for recreation (Betz et al., 2015, see also Figure 1).

For our remote sensing analysis we focus on the central part of the Naryn Basin as here the most extensive floodplain areas can be found due to the geomorphological character of the region (Betz et al., 2016). Area of interest (AOI) for the remote sensing data collection is defined with geographic coordinates (N41.450° E75.031°; N41.352°, E75.031°; N41.450°, E75.691°; N41.352°, E75.691°) and a total area of about 700 km2 (Figure 2). The Naryn river floodplain with a total area of 69.5 km² is selected for the land cover classification and further investigations (Figure 3a).

2.2 Satellite Imagery Acquisition and Preprocessing

Sentinel-2A images for the vegetation season 2016 were downloaded from the scientific data hub of the ESA Sentinel mission (ESA, 2017a). Satellite imagery from this platform is available as top-of-atmosphere (TOA) data. A detailed list of the used S2A scenes is given in Table 1. Atmospheric correction has been carried out by using the sen2cor processor, a Python tool for conducting atmospheric correction as well as cloud, cloud shadow and snow detection using the algorithms of Zhu et al., (2015). For the processing, the Sentinel Application Platform (SNAP) offers a comfortable open source solution and this desktop software is available for download from the ESA website (ESA, 2017b).

To minimize the processing time, the band subsets of the Area of Interest have been extracted from the original granules. The 20 and 60 m image bands have been resampled to 10 m resolution using the nearest neighbor method before the subset processing for the Area of Interest (AOI) (Figures 3a and 3b). Preliminary product quality check shows that all three single tile S2A images are cloud free for the selected Naryn river floodplain section. For this study, we define the floodplain as the part of a valley being connected to the recent hydrological and geomorphological processes in the river channel (Hupp and Osterkamp). The delineation has been performed via the visual interpretation of satellite imagery.

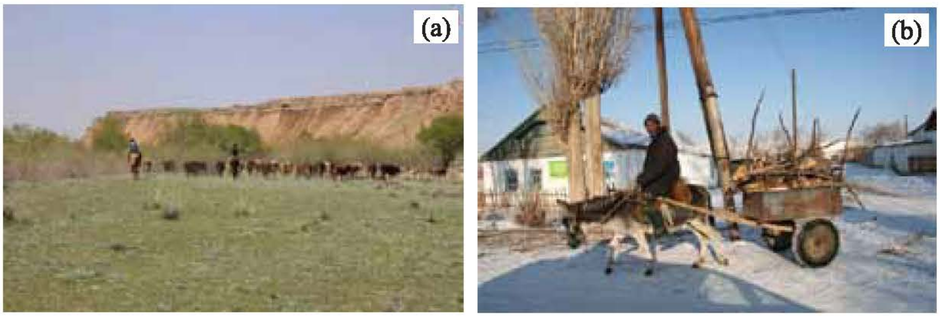

Figure 1: a) Grazing in floodplain forests; b) cutting of trees for firewood; Photos: F.Betz (l) and B.Cyffka (r)

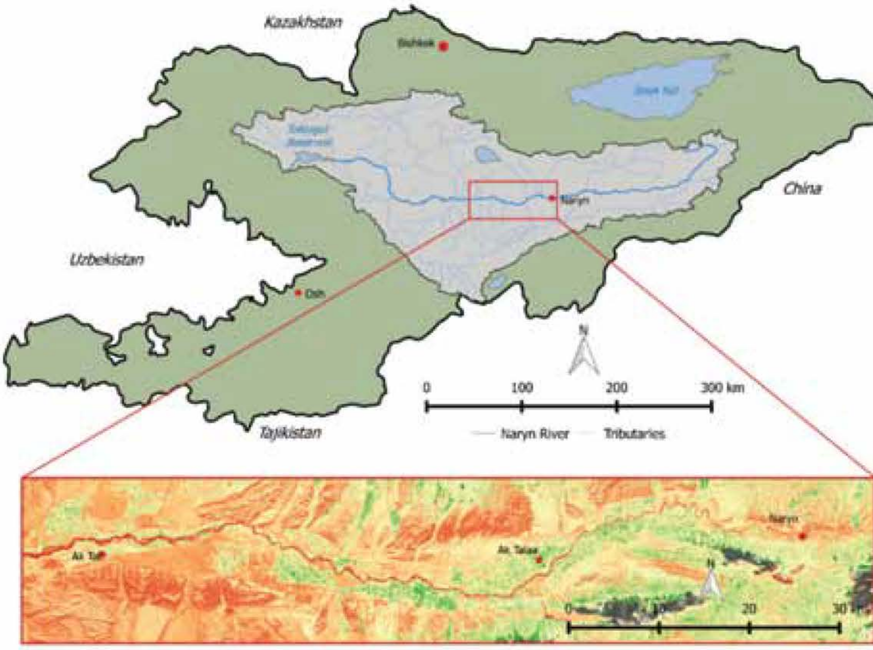

Figure 2: Overview over the study area: the detailed map shows a NDVI composite of the area of interest

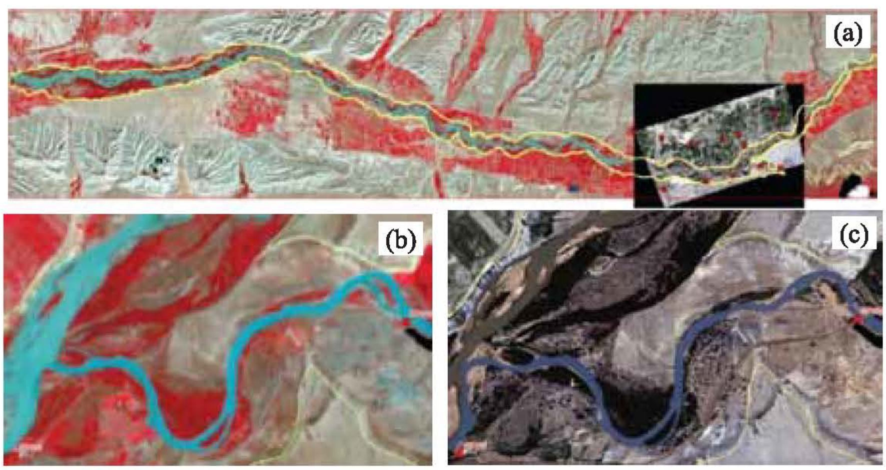

Figure 3: a) Multispectral satellite imagery for the Area of Interest (the floodplain is delineated with a yellow line); b) False color image (S2A, 2016, 10 m resolution); c) Natural color image (WV-2, 2014, 0.5 m resolution)

Table 1: Sentinel-2A MSI Granules used in this study

Sensing time	Processing level	Absolute Orbit No.	Tile No.
2016-06-10T05:52:06.158Z	Level-1C	A005050	T43TEF
2016-07-20T05:51:55.331Z	Level-1C	A005622	T43TEF
2016-08-09T05:54:34.076Z	Level-1C	A005908	T43TEF

For calibrating a supervised classification, a training data set has been generated during field surveys in the 2015-2016 vegetation seasons and via visual interpretation of a WorldView-2 image (14JUN29060129-S2AS) with 50 cm horizontal resolution. Georeferencing control and correction of this very high resolution image was realized by using 11 ground control points (GCP) positioned by a geodetic class Trimble R-8 GNSS receiver (Figure 3b). These GCPs have been used to confirm the declared 12.5-20 m geo-location accuracy of Sentinel-2 imagery (ESA, 2012).

2.3 Level-2A Image Processing

The Level-2A (L2A) processing includes an atmospheric correction applied to TOA S2A Level-1C products. L2A main output is an orthoimage bottom-of-atmosphere (BOA) corrected reflectance product. Atmospherically-corrected Level-2A images are produced using the Sen2Cor processor (version 2.3.1), developed by ESA to perform atmospheric, terrain, and cirrus correction of top-of-atmosphere Level-1C input data (ESA, 2017c).

The scene classification algorithm allows detection of clouds, snow and cloud shadows and generation of a classification map, which consists of different classes for clouds, shadows, cloud shadows, vegetation, bare soil or desert, water and snow (Figure 4). The classification algorithm is based on a series of threshold tests that use as input TOA reflectance of spectral bands, band ratios and indexes like Normalized Difference Vegetation Index (NDVI) and Normalized Difference Snow and Ice Index (NDSI). Preliminary analysis of the automated L2A classification shows that further image processing is needed to develop more detailed and specific land use/land cover classification.

The Normalized Difference Vegetation Index (NDVI) is the numerical indicator that uses the visible and near-infrared bands of the electromagnetic spectrum adopted to analyze remote sensing materials and assess live green vegetation content. NDVI has been used to estimate vegetation health, crop yields, pasture conditions and rangeland carrying capacities, among others. The NDVI algorithm subtracts the red reflectance values from the near-infrared and divides it by the sum of near-infrared and red bands. This formulation allows coping with the fact that two identical patches of vegetation could have different DN values if one were, for example in bright sunshine, and another under a cloudy sky. The bright pixels would all have larger values, and therefore a larger absolute difference between the bands. This is avoided by dividing by the sum of the reflectance values and the NDVI ratio for Sentinel-2 can be outlined as:

$$NDVI = (Band\ 8 - Band\ 4) / (Band\ 8 + Band\ 4)$$

Equation 1

Theoretically, NDVI values are represented as a ratio ranging in value from -1 to 1, but in practice extreme negative values represent artificial surfaces and water, values around zero represent bare soil and values over 0.6 represent dense green vegetation (Akkartal et al., 2004).

Each of the 3 Sentinel-2A images from a different sensing time demonstrate different vegetation indices for the same land plot because of the strong dependence of vegetation mass from seasons, agricultural planting and harvesting periods. Three different NDVI images received on June 10, July 20 and August 9, 2017, give different NDVI values for the same land plot and individually may lead to the wrong land cover classification (Figure 5a). Stacking of these three NDVI images with calculated maximum pixel NDVI values gives new raster with leveled NDVI for the improved agricultural land use classification (Figure 5b).

The preliminary analysis of three different NDVI images shows that calculated minimum pixel NDVI values are more suitable for the floodplain forestry classification. It can be explained by more stable vegetation mass of forested areas in comparison to the grass vegetation more vulnerable in the dry and wet vegetation periods of.

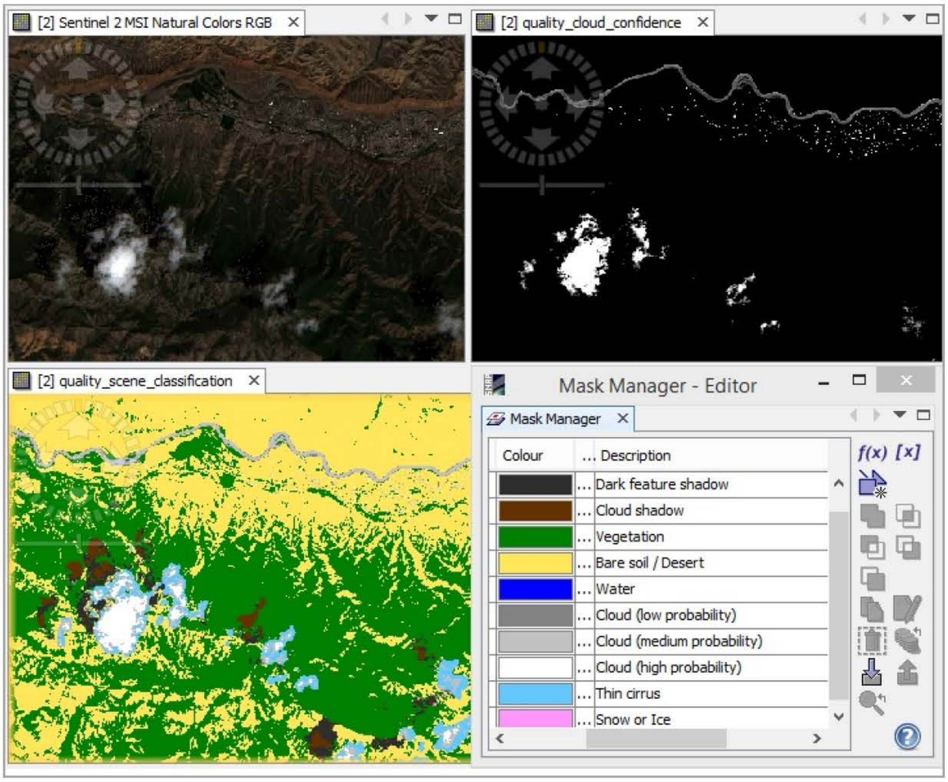

Figure 4: Level-2A product with RGB image, quality indicators and classification map

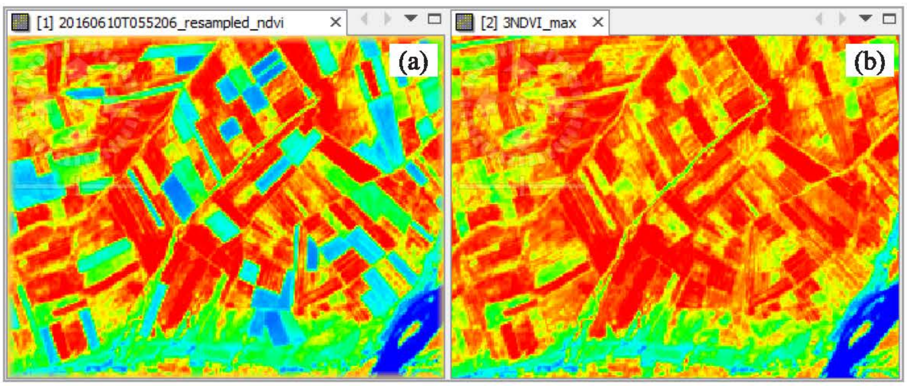

Figure 5: S2A image from June 10, 2016 (a) and the stacked image with maximum NDVI values (b)

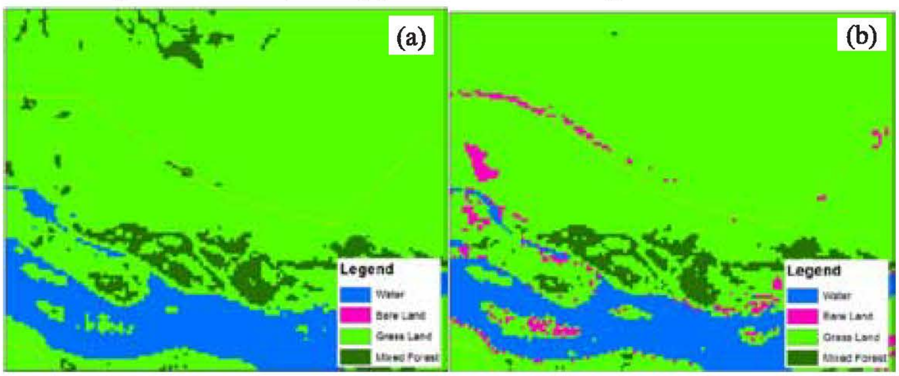

Figure 6: NDVI image from June 10, 2016 (a) and the stacked image with minimum NDVI values (b)

Classification of NDVI image from June 10 has many land plots misclassified as mixed forest areas (Figure 6a), and the off-season NDVI image with calculated minimum pixel NDVI value has removed cropped fields or grass vegetation from the mixed forest areas (Figure 6b).

Supervised classification of NDVI imagery and raster generalization. In this study, supervised Land use/Land cover (LULC) classification of SNAP processed NDVI imagery, with combined minimum values from three S2A scenes, is realized using field survey datasets, available WorldView-2 image and ArcGIS 10.4 software. For classification of each of the three Level-2A Sentinel-2A images, the study proceeded in the next steps: calculation of NDVI values for each of images, calculation of the combined maximum and minimum NDVI values, supervised classification of the NDVI image into LULC classes, enhancement of the classification and creation of a final LULC map.

Four LULC classes were selected for the supervised classification of the study area. Urban land and artificial surfaces are not significant and not included in the floodplain classification, rock surfaces and gravel/sand areas are classified as bare land, and mixed forest areas include trees and shrubs.

The verification of classification results by suing field data, WV-2 image and pie chart was used to display for understanding the different patterns of different land cover types (Figure 7).

Further generalization and enhancement of the classified image are realized using ArcGIS spatial analysis tools. There are many small areas of misclassified cells in the image needing cleaning up, and generalizing data to get rid of unnecessary details. Two basic tools available in the Spatial Analyst module applicable to removing artifacts from raster images are Boundary Clean and Majority Filter. Boundary Clean tool smooths the jagged boundaries by eliminating small patches of less significant groups of pixels of the same class, therefore simplifying the structure of raster images. The Majority Filter tool replaces cells in a raster based on the majority of their contiguous neighboring cells and satisfies two criteria before a replacement can occur.

The Majority Filter tool has been selected for the raster generalization based on the preliminary comparison and analysis of these two generalization instruments. The number of neighboring cells of a similar value must be large enough (either by being the majority, or half, of all the cells), and those cells must be contiguous around the center of the filter kernel. The second criterion concerning the spatial connectivity of the cells minimizes the corruption of cellular spatial patterns (Bartuś, 2014).

The majority filtering is determined by the results of observations of the cell values found around the central cell. The procedure selection is realized by defining the number of neighboring pixels involved in the analysis. The variable is set to "4", which means that the calculations have only involved pixels adjacent to the edges of the central cell, and the values of pixels located in the corners of the neighborhood are not be taken into account. After four iterations with majority replacement threshold the raster image has reached the acceptable level of stability without further changes.

The classified and generalized image in raster format was converted into vector format shapefile polygons using the ArcGIS Conversion. Cartographic smoothing with the PAEK smoothing algorithm is used for generalization of LULC class polygons to improve its aesthetic quality. The final versions of the thematic maps are prepared and printed out for the Naryn forestry department in different scales (Figure 8) and for the ecosystem service research purpose within the project "EcoCAR" (Betz et al., 2015).

3. Results

Sentinel-2A Level-1C images for the three months of 2016 vegetation season were downloaded and preprocessed applying the Sentinel Application Platform (SNAP). Output Level-2A (L2A) products have atmospheric, terrain, and cirrus correction of top-of-atmosphere L1C input data. SNAP has been used for the resampling of 20 m and 60 m image bands to 10 m resolution and further subset processing of all bands for the Area of Interest (AOI).

Use of multi-temporal Sentinel-2A images results in different vegetation indices for sample plots and LULC classifications, with maximum and minimum NDVI values facilitating an increase in classification accuracy depending the analysis purposes. Classification of the stacked image with maximum NDVI cell values will reduce the misclassification between crop and bare land due to the artificially impacted seasonal vegetation. Application of the stacked image with minimum NDVI values will improve the identification of mixed floodplain forest areas by excluding the grass land more affected by the seasonal drought. The supervised classification is used to identify four LULC classes for the study area as water surface, bare land, grass land and mixed forest areas with trees and shrubs. The final classification results are converted into polygon shape files for further map design and land use/land cover analysis.

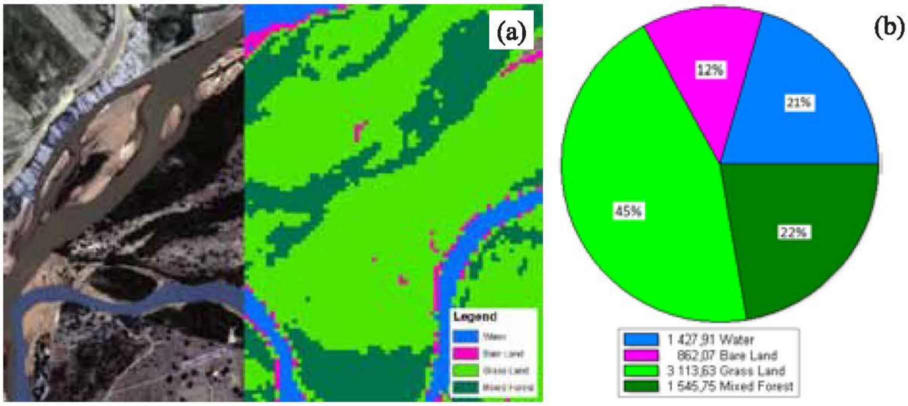

Figure 7: a) Land cover classification control; b) Floodplain land cover types (with areas in Ha and %)

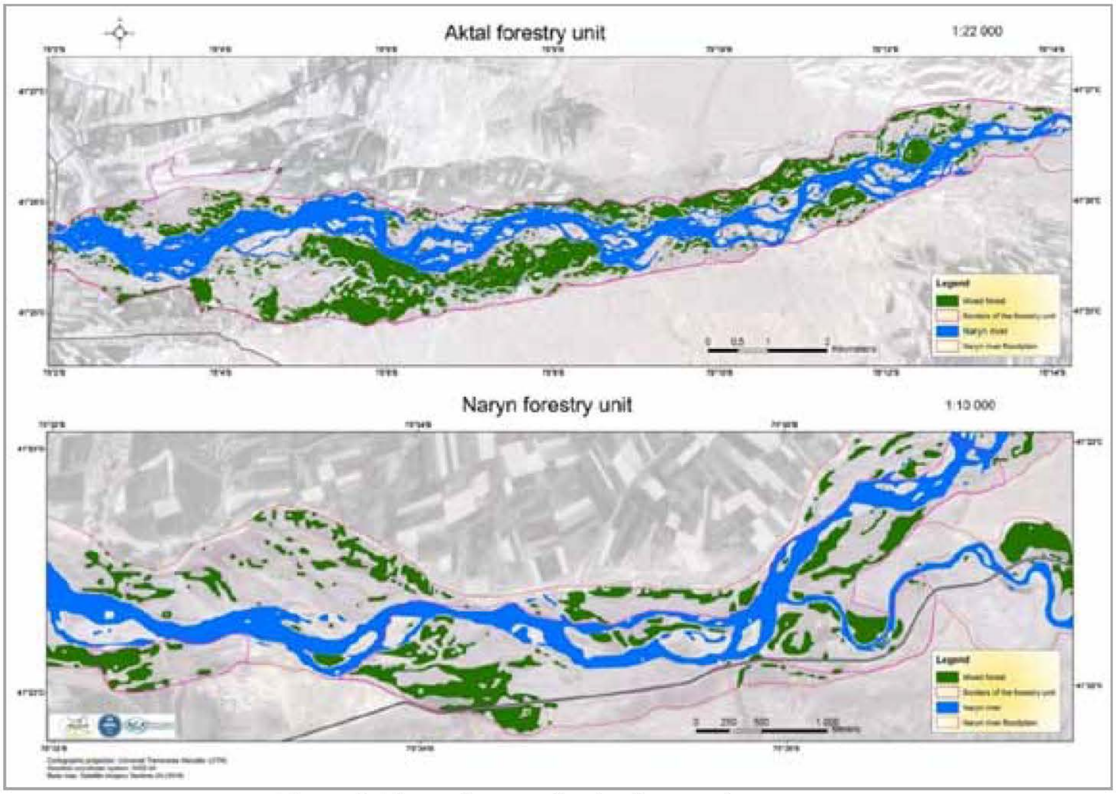

Figure 8: Thematic maps for the forestry department

4. Discussion and Conclusion

The classification accuracy assessment results for the study area indicate that the Sentinel-2A multispectral imagery can be used efficiently in forest studies, providing the fundamental data source for examining LULC changes as well as for the mapping and monitoring purposes. Such satellite image has high classification accuracy (90%-93%) for the investigation area with 25 sample plots. The major problem causing relatively low accuracy compared to the very high resolution imagery classification was the misclassification between grass vegetation and mixed forest due to their complex vegetation stand structure and species composition, and between initial succession (other vegetation) and mixed agro-pasture due to the lack of a clear boundary between them.

Application of the high resolution Sentinel-2A images, enhanced by using different image correction and improvement tools and algorithms, make it as one of the most advantageous and accessible multispectral optic satellite system for the forest mapping and monitoring.

Acknowledgments

This study is part of the project "*Ecosystem Assessment and Capacity Building along the Central Asian Rivers Tarim and Naryn*" funded by the Volkswagen Foundation. The authors would like to thank the European Space Agency (ESA) for the provision of Sentinel-2A data and Sentinel Application Platform.

References

Akkartal, A., Türüdü, O. and Erbek, F. S., 2004, Analysis of changes in Vegetation Biomass using Multitemporal and Multisensor Satellite Data. *ISPRS Archives*. Vol.XXXV Part B8, 181-185.

Bartuś, T., 2014, Raster Images Generalization in the Context of Research on the Structure of Landscape and Geodiversity. *Geology, Geophysics & Environment*. Vol. 40, No. 3, 271-284.

Betz, F., Rauschenberger, J., Lauermann, M. and Cyffka, B., 2016, Using GIS and Remote Sensing for Assessing Riparian Ecosystems along the Naryn River, Kyrgyzstan. *International Journal of Geoinformatics*. Vol. 12, No.4, 25-30.

Betz, F., Cyffka, B., Halik, U., Kurban, A., Chymyrov, A., Baibagyshov, E. and Ding, J., 2015, GIS for Environmental Management along the Central Asian Rivers Tarim and Naryn. *Proceedings of the GIS in Central Asia Conference – GISCA 2015 "Geospatial Management of Land, Water and Resources"*, May 14-16, TIIM, Tashkent, Uzbekistan, 13-18.

Chymyrov, A., Baibagyshov, E., Degembaeva, N., Ismailov, T., Urmambetova, T., .Aiypov, B., 2016, Study of the Naryn River Floodplain Forest Ecosystem by using Very High-Resolution Satellite Imagery. Forest Ecosystems under Climate Change: Biological Productivity and Remote Monitoring. Compendium of research papers/Executive Editor Prof. E.A. Kurbanov – Yoshkar-Ola: Volga State University of Technology, Russia, 2016, 100-106.

Clerici, N., Weissteiner, C. J., Paracchini, M. L., Boschetti, L., Baraldi, A. and Strobl P., 2013, Pan-European Distribution Modelling of Stream Riparian Zones Based on Multi-Source Earth Observation Data. *Ecological Indicators*. 24: 211-223.

Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., Hoersch, B., Isola, C., Laberinti, P., Martimort, P., Meygret, A., Spoto, F., Sy, O., Marchese, F. and Bargellini, P., 2012, Sentinel-2: ESA's Optical High Resolution Mission for Scientific Observations of Ocean, Cryosphere and Land. *Remote Sensing of Environment*. Vol. 120, 91-101.

ESA, 2012, Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services (ESA SP-1322/2 March 2012).

ESA, 2017a, Copernicus Open Access Hub. https://scihub.copernicus.eu/dhus [accessed on May 10, 2017b].

ESA, 2017b, Sentinel Application Platform (SNAP). http://step.esa.int/main/download [accessed on May 10, 2017].

ESA, 2017c, Sen2Cor. http://step.esa.int/main/third-party-plugins-2/sen2cor [accessed on May 10, 2017].

Gomez, C., White, J. C. and Wulder, M. A., 2016, Optical Remotely Sensed Time Series Data for Land Cover Classification: A Review. *ISPRS Journal of Photogrammetry and Remote Sensing*. Vol. 116, 55-72.

Hupp, C. R. and Osterkamp, W. R., 1996, Riparian Vegetation and Fluvial Geomorphic Processes. *Geomorphology*. Vol. 14, 277-295.

Karthe, D., Chalov, S. and Borchardt, D., 2015, Water Resources and their Management in Central Asia in the Early Twenty First Century: Status, Challenges and Future Prospects. *Environmental Earth Science*. 73(2): 487-499.

MA, 2005, Millennium Ecosystem Assessment. Ecosystems and Human Well-Being. A Framework for Assessment. Washington. Island Press.

Ozdogan, M. and Kurban, A., Chapter 15: The Effects of Spatial Resolution on Vegetation Area Estimates in the Lower Tarim Basin, NW China. In: Chen, J., Wan, S., Henebry, G., Qi, J., Gutman, G., Sun, G. and Kappas, M., (eds.) Dryland East Asia (DEA): Land Dynamics Amid Social and Climate Change. HEP-De Gruyter Publishers.

Radoux, J., Chome, G., Jaques, D. C., Waldner, F., Bellemans, N., Matton, N., Lamarche, C., d'Andrimont, R. and Defourny, P., 2016, Sentinel-2's potential for Sub-Pixel Landscape Feature Detection. *Remote Sensing*. Vol. 8, No. 6, 488. Doi: 10.3390/rs8060488.

Vorobyev, O., Kurbanov, E., Gubaev, A., Demisheva, E., 2015, Method of Stepwise Classification of Satellite Images for the Thematic Mapping of Forest Cover. *Bulletin of the Volga State University of Technology*, Russia, Vol. 28, No. 4, 57-72.

Zhu, Z., Wang, S. and Woodcock, C. E., 2015, Improvement and Expansion of the Fmask algorithm: Cloud, Cloud Shadow, and Snow Detection for Landsats 4-7, 8, and Sentinel 2 Images. *Remote Sensing of Environment*. Vol. 159, 269-277.