Multi-temporal monitoring of cotton growth through the vegetation profile classification for Tashkent province, Uzbekistan

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Abstract

As satellite data of the Earth surface seems to be of vital importance for many applications, classification of land use and land cover has been found to vary dramatically in different approaches. In this paper, modified classification algorithm of remote sensing data is presented for processing medium and high spatial resolution satellite images like Landsat and Sentinel in Tashkent province of Uzbekistan. The results of NDVI (Normalized difference vegetation index) profile analysis via Spectral Correlation Mapper classification are shown for the period 1994-2017. It is implied, that combination of optical and radar data with application of Spectral Correlation Mapper classification improve the results of classification for a specific dataset by considering such factors as overall classification accuracy and time and labor involved.

Highlights for public administration, management and planning:

- The Spectral correlation classification method of NDVI profiles is presented resulting in higher accuracy of cotton growth-related land use estimations.
- A change in agricultural land use of Uzbekistan since the 1990s was detected, in spite of the decreasing trend of cotton plantations after 2004.
- The presented approach may assist to reveal the effects of agricultural policies and environmental change on land use.

Keywords

Agriculture,
Land use classification,
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NDVI profile,
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1 Introduction

History of the cotton production is quite long in Uzbekistan and its production and export is one of the leading branches of agriculture. If in Central Asia 2 million tons of cotton fiber are grown per year, 1.4 million of them are Uzbek fiber. Another name of cotton in Uzbekistan is “white gold”. Nowadays, cotton-wheat-rice or cotton-wheat crop rotations are the main crop system in Uzbekistan (Djanibekov et al. 2010). During the years of sovereign development in the republic, the task was set - to achieve grain independence. The structure of the acreage was changed, the farms gained autonomy and could themselves decide which crop to sow. In such conditions true understanding of the LULC spatiotemporal change process in Uzbekistan since 1991 is in importance (Kahriz et al. 2019).

Remote Sensing images in recent years became an indispensable tool in a variety of surface land use studies. According to some authors (Seto et al. 2002), land use and land cover are often used interchangeably, but the two concepts are not exactly the same. The latter measures the physical attributes or characteristics of the Earth's surface, while the former describes how land cover is utilized. Remote Sensing (RS) detects land cover, not land use, though in most cases one can derive land use from land cover. RS change-detection studies use the two concepts interchangeably (e.g. Heikkonen & Varfis 1998; Muttitanon & Tripathi 2005) because land use often corresponds to land cover. For instance, in cultivated environments, cropland could describe land use type, while at the same time it is a form of land cover. In such scenarios, the two concepts could be considered as synonymous (Kiage et al. 2006). In this article the term land use will be used.

Fig. 1 Study area

Satellite-based RS offers an accurate, time and cost-efficient tool for monitoring and mapping crop allocation at different scales (e.g., [Conrad et al. 2011](#); [GEOSS 2009](#)). Essentially, last research on agricultural land use shows that over the last decade interest of using RS satellite imageries are increased widely rather than field data measurement on the ground in Central Asia ([Hamidov et al. 2016](#)). At the same time, the need to obtain reliable data on the surface is constantly increasing as a consequence of constantly observed changes in the landscape.

The requirement to obtain reliable results in solving the problem of classification determines the need for processing procedures with probabilistic characteristics. Modern remote sensing systems have a different number of spectral channels, making it difficult to conduct a visual image classification, so the classification algorithms are implemented in various software designed to work with remote sensing data.

Each of them provide different level of overall accuracy of land cover classification. For instance, some determine 87% accuracy and 98% when classified only into two classes like water/soil ([Edlinger et al. 2012](#)), other set 96.17% after merging with high-resolution images and with the standard type only 75.88% ([Yeshaneh et al. 2013](#)), researchers in China showed 80.89% accuracy with the additional use of four different indices ([Tian et al. 2014](#)). At the same time [Platonov et al. \(2008\)](#) and [Zhang et al. \(2011\)](#) show NDVI threshold value for several crop types in agriculture and emphasized on importance of phenological crop development knowledge on detecting spectral signatures of certain crops in Central Asia. [Conrad et al. \(2011\)](#) analysed land use classification assessment

with using NDVI methods by utilizing MODIS satellites with low spatial resolution 250 m, in Khorezm province of the Uzbekistan. In this way we found a lack of information in regard to the best algorithms for land use classification analysis, especially for cotton growth.

The major objectives of this research are to evaluate the effectiveness of Spectral correlation mapper classification method in combination with NDVI optical and radar data for monitoring of cotton growth in Uzbekistan in 1994–2017.

2 Materials and methods

2.1 Study area

This study was conducted in Orta Chirchiq district of Tashkent Region in Uzbekistan, which was established in 1926. The capital of the district is Toytepa town. The population of the district is about 163 400 people and the total area is 510 km² ([Fig. 1](#)). The corresponding time zone is UTC+5 (UZT). On considerable part of the district, the vegetation period of plants exceeds 200 days. Favorable climatic terms allow tilling a cotton plant and other heat-loving cultures, get 2–3 harvests of vegetables in a year ([Glazirin et al. 1999](#)).

2.2 Data

The data used in the study include Landsat and Sentinel raster images that were obtained in the open Internet resources of the United States Geological Survey (USGS) Center for Earth Resources Observation and Science (EROS) and Sentinel

Table 1 Sensors characteristics

	Landsat TM5	Landsat 7ETM+	Landsat 8OLI	Sentinel 2	Sentinel 1A
Launched	March 1984	April 1999	February 2013	June 2015	April 2014
Source	NASA	NASA	NASA	ESA	ESA
Swath wide	185 km	185 km	185 km	290 km	250 km
Orbit	705 km	705 km	705 km	786 km	786 km
Temporal resolution	16 days	16 days	16 days	2–5 days	2–6 days
Spatial resolution	30/120 m (VIS/TIR)	15/30/60 m (PAN/VIS/TIR)	15/30/100 m (PAN/VIS/TIR)	10/20/60 m	5x20 m
Spectral resolution (bands)	7	8	11	13	4

ESA sources. It is important to note, that Landsat is an operational imaging system and each scene is ordered in a so-called World Reference System (WRS), where Orta-Chirchiq district is located at path 154 and row 31. The spatial resolution of Landsat images varies from 15 m in panchromatic band, to 30 m in the rest bands not taking into account thermal layers. Approximate scene size is 170 km north-south by 183 km east-west. More descriptive information about used satellites are shown in (Table 1).

The total temporal range of acquired data corresponds to April – November due to the phenological conditions and higher NDVI values in this period of the year (Table 2). Other useful data included the co-registered vector administrative boundary of Orta-Chirchiq district, which was generated by ESRI ArcGIS 10.2 software based on scanned topography map, and later was used as masks to get subset-images of the study area. At the same time for the classification model expert information

on the phenological crop development in the region was very important. This information is expected to determine mainly the spatial and temporal land use distribution in the study area. Field data were collected between June and August in 2017 and 105 ground control points were collected for the further use in accuracy assessment. Google Earth and Google map data as well as local authorities wheat map for 2017 were used as a supplementary source of information.

2.3 Conceptual framework

The experiment was performed combining Spectral Correlation Mapper classification of NDVI profile to Sentinel radar and optical images. The flow chart of the proposed methodology is presented in Fig. 2, comprising the following major steps: data collection, preprocessing, NDVI calculation, SCM classification, merging to Sentinel images, results analysis (Fig. 2).

Table 2 Landsat (LT5 – Thematic Mapper, LT7 – ETM+ and LC8 – Landsat OLI) images, used for the classification

	1994	1999	2009	2014	2017
April		LT5 April 13	LT5 April 8 LT5 April 24	LC8 April 6 LC8 April 22	LC8 April 14 LC8 April 30
May	LT5 May 1 LT5 May 17		LT5 May 26	LC8 May 24	LC8 May 16
June	LT5 June 2		LT5 June 11 LT5 June 27	LC8 June 25	LC8 June 1
July	LT5 July 4 LT5 July 20	LT7 July 10	LT5 July 29	LC8 July 27	LC8 July 3 LC8 July 19
August	LT5 August 21	LT5 August 19 LT7 August 27		LC8 August 12 LC8 August 28	LC8 August 12
September	LT5 September 6			LC8 September 29	LC8 September 16 LC8 September 21
October	LT5 October 8		LT5 October 17		
November			LT5 November 18		

Fig. 2 Flowchart of the research

The following land use/cover classes were used for interpreting the satellite images: cotton, rice, wheat, gardens including other crop types and small parts of the high-vegetated areas, and settlements including residential area.

2.4 Data processing

Six temporal datasets (1994, 1999, 2004, 2009, 2014, 2017) were chosen to identify changes in land use of Tashkent province. However due to the problems on Scan Line Corrector at Landsat 7 ETM+ data during 2004 were not appropriate to use in the procedure, so only five years were taken for the further analysis.

Thirty-seven Landsat images (Table 2) were pre-processed by ATCOR module in ERDAS software to reduce atmospheric haze (light fog), atmospheric and topographic correction. Data had been enhanced in the pre-processing stage by different filters like high pass and medium filter in order of attenuation the effects of noise and improve the data quality spectrally and spatially (Lillesand et al. 2015).

NDVI images were created with the use of NIR and RED layers of Landsat and Sentinel2 satellites. Received NDVI images from multiple time steps within one vegetation period were stacked and displayed. The NDVI profiles of the visually separable classes were compared with phenological stages of the typical crops from the study area. Five typ-

ical spectral curves were detected in the received image: one peaked in May, but showed low values afterwards (yellow); another with peak in August acquisitions (brown); one with higher peak in August and relatively very low NDVI in May (blue); one with increasing values in spring but with stable decreasing curve in the rest period (green) and the last with NDVIs increasing only to soil line level 0.3 and not higher (red). On the basis of expert knowledge and presented classes in the study area these colors were corresponded as follows: yellow - wheat, brown - cotton, blue - rice, green - gardens and red - residential area (Fig. 3). The bands on the graph correspond to the NDVI layers in 2017 as follows: 1 - April 14, 2- April 30, 3 - May 16, 4 - June 1, 5 - July 3, 6 - July 19, 7 - August 12, 8 - September 16, 9 - September 21.

Fig. 3 NDVI profile for April - September 2017

The Spectral correlation mapper (SCM) classification was conducted and assessed the recognition of figures with negative relationship and produces better outcomes for elimination of shading impact (De Carvalho & Meneses 2000). These classification methods for feature spectra is based on a comparison of the spectral image with a reference spectrum (endmembers or spectral libraries).

The well separated training polygons were digitized on-screen dependent on territory information obtained during field work. The pixels in the polygons that were chosen as illustrative of each class were plotted in spectral space and a visual check was made that all classes could be isolated in no less than one band combination.

As the spatial resolution of used Landsat layers is 30 by 30 meters, boundaries between the fields suffered the problem of classification and so merging of NDVI profile for 2017 was applied to Sentinel 2 image of August 8. Landsat NDVI layers were re-sampled to the higher resolution and 10 layers in total for 2017 and were analyzed later on (Fig.4).

At the final step, radar Sentinel 1 image from June was used in order to calculate radar NDVI by comparison VV and VH polarizations. The result of subtraction of these polarizations was analyzed for further visual interpretation and comparison. For accuracy assessment 105 random sampling points in Water users Association “Sof oq oltin” of Orta Chirchiq district were collected. The number of the points were evaluated in accordance to the formula, introduced by Cochran (1997).

$$n = \left(\frac{\sum_{i=1}^k w_i s_i}{S(O)} \right)^2 \quad (1)$$

where n - number of the pixels in the area; S(O) - standard error; w_i - part of i-class from the total area; s_i - standard deviation of i-class calculated as

$$s_i = \sqrt{U_i(1 - U_i)} \quad (2)$$

As n usually too large in comparison to the rest parts of the formula, the second term is not taken into account. During the sample determination, the values of some indicators from formula 1 are set based on the previous experience of the researcher. From these considerations, for each category, the user error values (U_i) specified in the Table 3 are selected. The standard error of the total accuracy indicator is also independently selected (in this case, the reliability level was set as 95% ($S(O) = 0.05$)).

Table 3 Values for control points number evaluation

	N	W	U	$\sqrt{U(1 - U)}$
wheat	10083	0.3707	0.95	0.22
cotton	10007	0.3679	0.85	0.36
rice	925	0.0340	0.75	0.43
gardens	1041	0.0383	0.65	0.48
residential area	5145	0.1891	0.99	0.10
Total	27201	1.0000		

3 Results and discussion

Classified thematic maps were produced, accuracy was tested and the post classification process was carried out. Spatial patterns of agricultural classes showed various land use clusters and at the same time, it was found that cotton, wheat and rice fields were scattered throughout the region.

Analysis of radar Sentinel1 data allow to conclude that VH polarization in combination with others can be used better to model NDVI in the early stages of vegetation. Compared to VV, VH polarization is more suitable for classifying crops, reducing noise. The double polarization VV - VH allows you to get more accurate results than the double polarization HH - HV.

By applying the SCM supervised classification of NDVI profiles and improvement of the result by combination and comparisons to Sentinel optical and radar data it was investigated that overall classification accuracy improved for 2017 from 89 to 93% with a kappa coefficient varying from 0.89 to 0.95. The kappa coefficient represents the level of agreement between the training samples and land use/cover values in the classified image. The maximum value for kappa occurs when the observed level of agreement is 1. A kappa coefficient greater than 0.80 represents very good level of agreement.

Table 4 summarizes the producer's and user's accuracies for each of five classes before and after Sentinel data. The user's accuracy was calculated by dividing the number of all correctly classified pixels of a class by the sum of all pixels which had been assigned to that class and producer's accuracy was calculated by dividing the number of all correctly classified training pixels of a class by the sum of training data pixels for that class; it indicates the probability of a training pixel being correctly classified (Congalton 1991). The producer's and user's accuracies for 2017 were estimated greater than 81%.

Fig. 4 Image merging (from left to right a) Landsat NDVI image, b) Sentinel 2 image, c) merged image.

Table 4 Mean producer's and user's accuracies in 2017

		Cotton	Wheat	Rice	Gardens	Residential
Producer's accuracy	before	86%	95%	90%	85%	86%
	after	91%	95%	100%	86%	91%
User's accuracy	before	90%	95%	86%	81%	90%
	after	95%	95%	90%	86%	91%

At least one acquisition of each month was necessary for a reliable overall accuracy and so the lowest result for 1999 (73% overall accuracy) could be caused by the absence of images for the period May-June.

The results of the classification show in general a fair congruence with the governmental district level area statistics from 1994. Because of lack in statistical data, comparison of cotton fields was evaluated only for 1994-2014. By implementation of Sentinel data analysis user's accuracy for cotton

improved from 90 to 95% while producer's accuracy from 86 to 91% respectively. The results obtained at the district level showed a decrease of cotton fields' area on 2 714 ha in accordance to remote sensing and on 3 094 ha to statistical data. Prevalence of remote sensing data in hectares could be explained, probably by the inclusion of adjacent territories between the fields and further research is needed, which will mainly concentrate on the improvement of boundaries evaluations. Correlation between ground truth data and satellite data was found as 0.99 (Fig. 5).

4 Conclusion

Cotton is considered as a one of the most important amongst the essential products in Uzbekistan, which plays a prevailing role in economy of the country. Reliable remote sensing data help to produce more detailed spatial data. Spectral correlation classification method of NDVI profiles

Fig. 5 Comparison of statistical (blue line) and classification (red line) data

and combination of the results with Sentinel optical and radar data allowed to improve overall classification accuracy for 2017 from 89 to 93% with a kappa coefficient varying from 0.89 to 0.95. The results of the research demonstrated a noteworthy change in land use of Uzbekistan since the 1990s, in spite of the fact that there additionally has been a decreasing trend of cotton plantations after 2004. The appeared changes are connected to the changes in strategy of the country and progress to the grain autonomy.

The combination of different resolutions makes it possible to model the location of major crops based on NDVI values. In order to achieve a land use estimation with an accuracy higher than 85%, at least seven scenes per year were necessary for the analysis. Improved confusion matrices of the classifications showed overall accuracies ranging between 89% and 93%. Finally, an overlay of the classification results of 2017 in Google Earth (recorded in the same year) confirmed, that the results are reliable.

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