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ORIGINAL ARTICLE

Quantitative assessment of 2014–2015 land-cover changes in Azerbaijan using object-based classification of LANDSAT-8 timeseries

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Abstract The main goals of this study are the object-based land-cover classification of LANDSAT-8 satellite imagery of 2014 and 2015, the quantitative assessment of gross and net changes of agricultural land, built-up areas, forest, bare soil and forest between 2014 and 2015, the quantification of the Normalized Difference Vegetation Index (NDVI) rates within these land-cover classes, and the change detection analysis between the NDVIs. The achieved overall accuracies of object-based classification for the 2014 and the 2015 land-cover maps were 82 and 87 %, respectively. Therefore, the achieved accuracies were considered to be acceptable for quantified change detection analyses. For the gross areas of agricultural land, forest and built-up areas an increase was observed. The agricultural gross area was 30,911 km^2 in 2014 and 31,999 km^2 in 2015. The gross area of the built-up land increased from 12,550 to 13,548 km^2. The gross area of forest land changed from 8211 to 9175 km^2. A decrease was observed in the gross area of grassland from 28,229 to 24,925 km^2. This was primarily related to the land-cover shifts driven by agricultural activities. The gross areas of bare soil and water bodies did not change significantly. The net change analysis, however, revealed significant differences in comparison to gross change areas for both gains and losses of the land-cover classes. The net change analysis revealed positive net changes of 7229, 5576, 1337, 399, 951 km^2 for agricultural land, forest, built-up areas, bare soil and water bodies, correspondingly. A negative net change of 2198 km^2 was observed for grassland. This allows to conclude that the negative net change of grassland was related with the significant changes of grassland into agricultural land. No significant net changes were observed for the bare soil land-cover class. The classification of NDVIs derived from 2014 to 2015 LANDSAT-8 OLI satellite images showed that the vegetation cover of agricultural and built-up land-cover increased for the low (0.1–0.2) and medium (0.2–0.3) and decreased for the high NDVI values (0.3–1). The area of high (0.3–1) NDVIs in the forest land-cover was observed to be higher in 2015 than in 2014. A reduction in the low (0.1–0.2), medium (0.2–0.3) and high NDVI values (0.3–1) was observed for the grasslands land-cover. The reductions of the high NDVI rates (0.3–1) observed for agricultural, build-up and grasslands land-cover types may be related to agricultural and industrial activities and also to climate change impacts. For the entire coverage of Azerbaijan, positive and negative NDVI changes of 3170 and 3859 km^2 respectively were observed.

Keywords Land-cover · Change detection · Gross and net change · LANDSAT-8 (OLI) · Segmentation · Classification

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Introduction

The land-cover changes in Azerbaijan are controlled by a number of natural and social drivers such as intensive agricultural activities, increasing temperatures, growing industrial activities, overgrazing, shrinking glaciers, reduction and redistribution of river flows and decreasing rainfalls and snowfalls. The main goal of the present research was to study the changes of land-cover classes and NDVIs between 2014 and 2015 in Azerbaijan. The detailed goals of this research were following:

1. Object-based segmentation and classification of agricultural land and built-up areas, bare soil, grassland and water bodies based on LANDSAT-8 satellite images acquired for the vegetation peak seasons of 2014 and 2015 in Azerbaijan.
2. Assessment of classification accuracy of the land-cover classes using 660 randomly distributed control points and error contingency matrix.
3. Quantification of land-cover gross and net changes and of net land-cover gains and losses using change-detection overlay-analysis.
4. Quantification of NDVI values of the 2014 and 2015 land-cover classes for the evaluation of vegetation cover changes.
5. Change detection of NDVIs between 2014 and 2015 for the assessment of spatiotemporal changes in the vegetation cover.

The previous studies of land-cover in Azerbaijan mainly concentrated on the use of supervised remote sensing maximum likelihood classification techniques using 1998 and 1999 LANDSAT 5 and 7 TM satellite images (Manakos and Braun 2014; İsmatova 2005). Unfortunately, the results of the studies were not accessible for comparative analysis. The novelty of the present research for Azerbaijan is the application of object-based segmentation and classification techniques using 2014 and 2015 LANDSAT-8 satellite images for

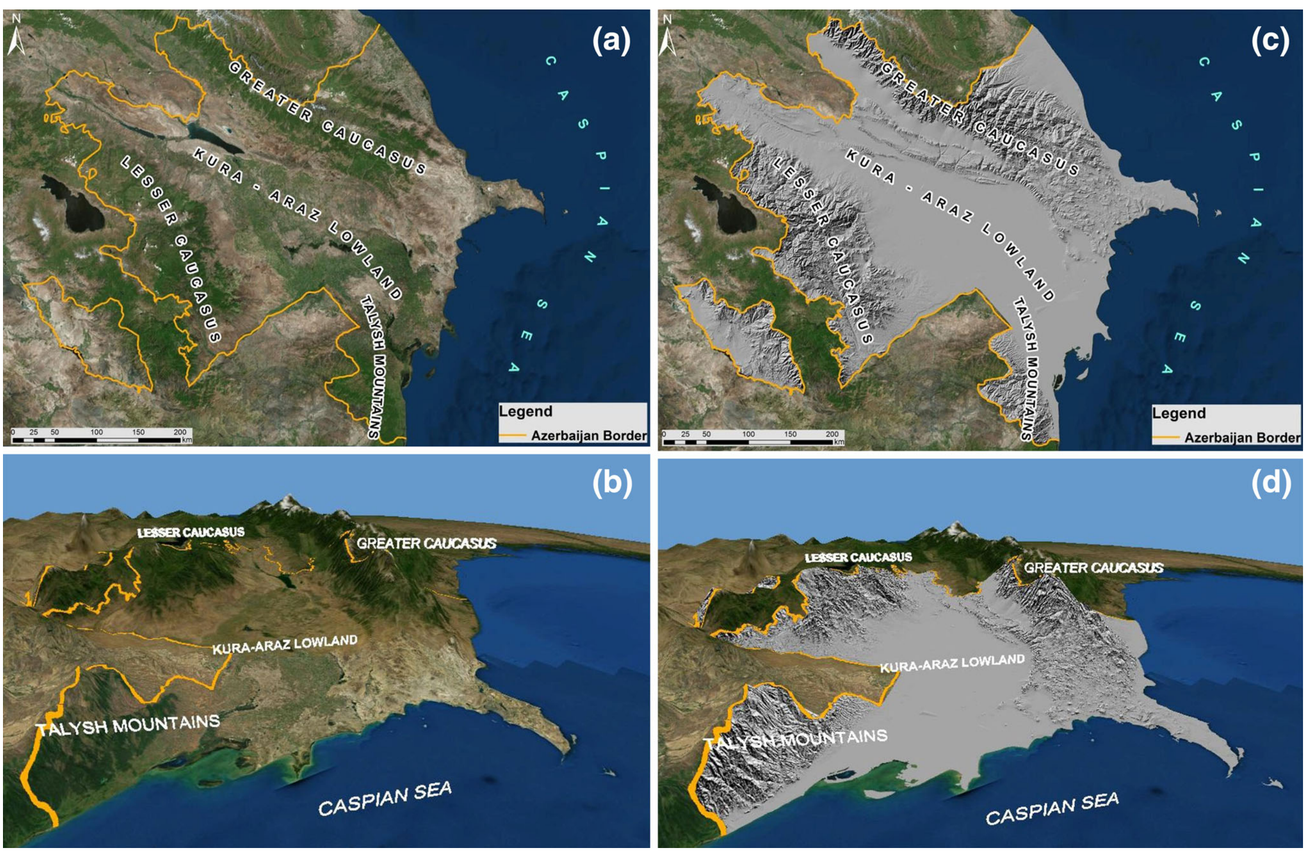


Fig. 1 **a** Satellite image of Azerbaijan; **b** 3D view of satellite image for Azerbaijan; **c** relief shading of Azerbaijan; **d** 3D view of hill-shading of Azerbaijan

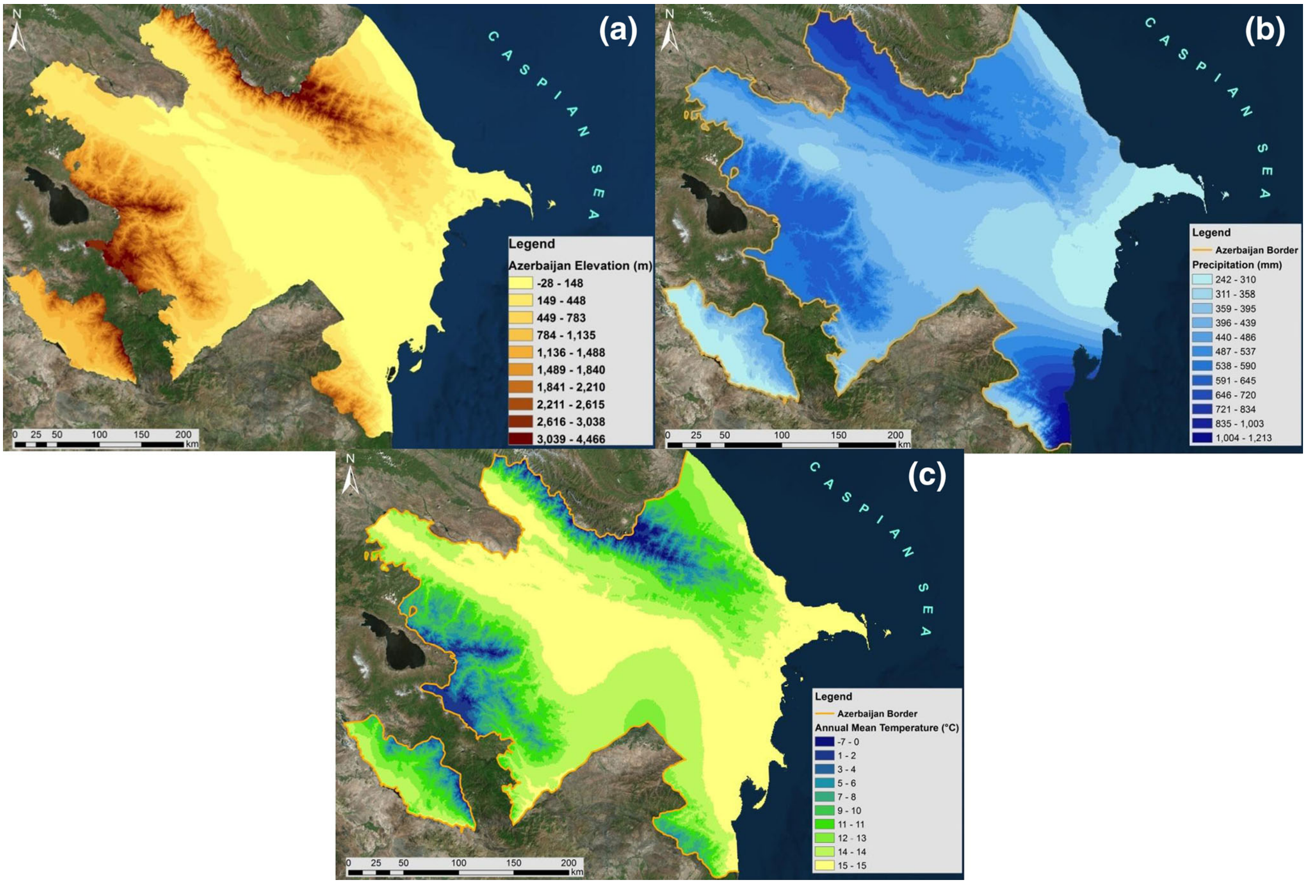
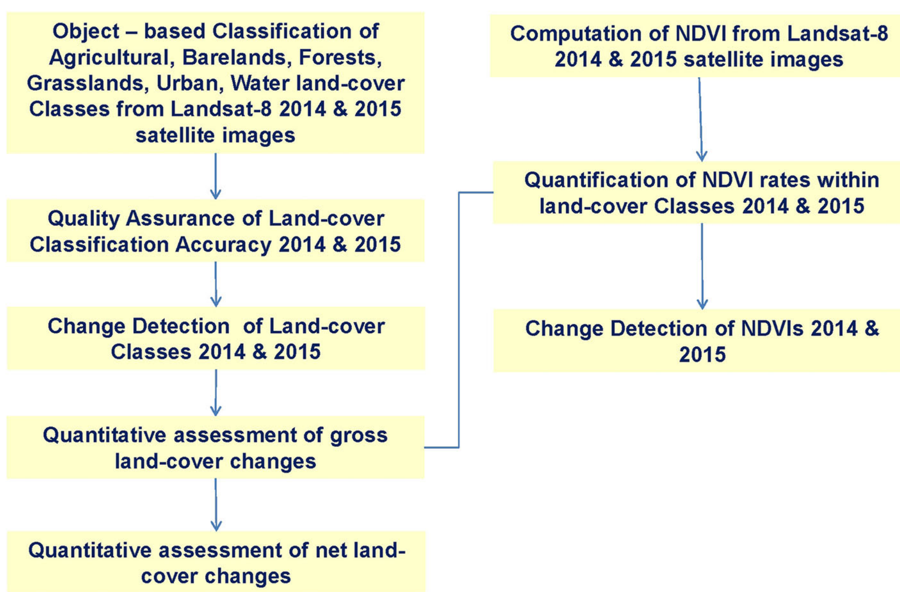


Fig. 2 **a** Elevation model of Azerbaijan; **b** precipitation of Azerbaijan (*Data source* Hijmans et al. 2005); **c** annual air temperature (*Data source* Hijmans et al. 2005)

Fig. 3 Workflow for object-based segmentation, classification, quality assurance and land-cover analysis



the development of the land-cover in Azerbaijan. The previous studies revealed a better performance of land-cover classification accuracy and reliability using the object-based classification in comparison to maximum likelihood pixel-based classification techniques (Robertson and King 2011; Whiteside et al. 2011; Whiteside and Ahmad 2005; Dehvari and Heck 2009; Cleve et al. 2008; Gao and Mas 2008; Matinfar et al. 2007; Myint et al. 2011; Willhauck et al. 2000; Mansor et al. 2002; Oruc et al. 2004; Darwish et al. 2003; Mitri and Gitas 2002; Niemeyer and Canty 2001; Esch et al. 2003; Ghobadi et al. 2012; Sande et al. 2003; Liu and Xia 2010). Therefore, the object-based classification technique was selected for this study to map the Azerbaijan land-cover for 2014 and 2015 based on LANDSAT-8 satellite images acquired during the vegetation peak seasons.

Study area

Azerbaijan is characterized by a diverse landscape with two major landforms: plains and mountains. Mountains cover 60 % of the total area of the Republic of Azerbaijan. Greater, Lesser Caucasus and Talysh Mountains surround the Kura-Araz Lowlands in the north, west and south-east (Fig. 1a–d). The altitude of Azerbaijan varies from −28 in Caspian Sea coastal areas to 4466 m in the mountains (Fig. 2a). Precipitations amount to 200–300 mm in Kura-Araz Lowlands, 600–800 mm on north-eastern slopes of Greater and Lesser Caucasus, and 1200–1300 mm on southern slopes of Greater Caucasus at a height of 2000–2500 m (Fig. 2b). The climate in Azerbaijan is significantly influenced by its geographical position, its landscape and the Caspian Sea. Semi-desert,

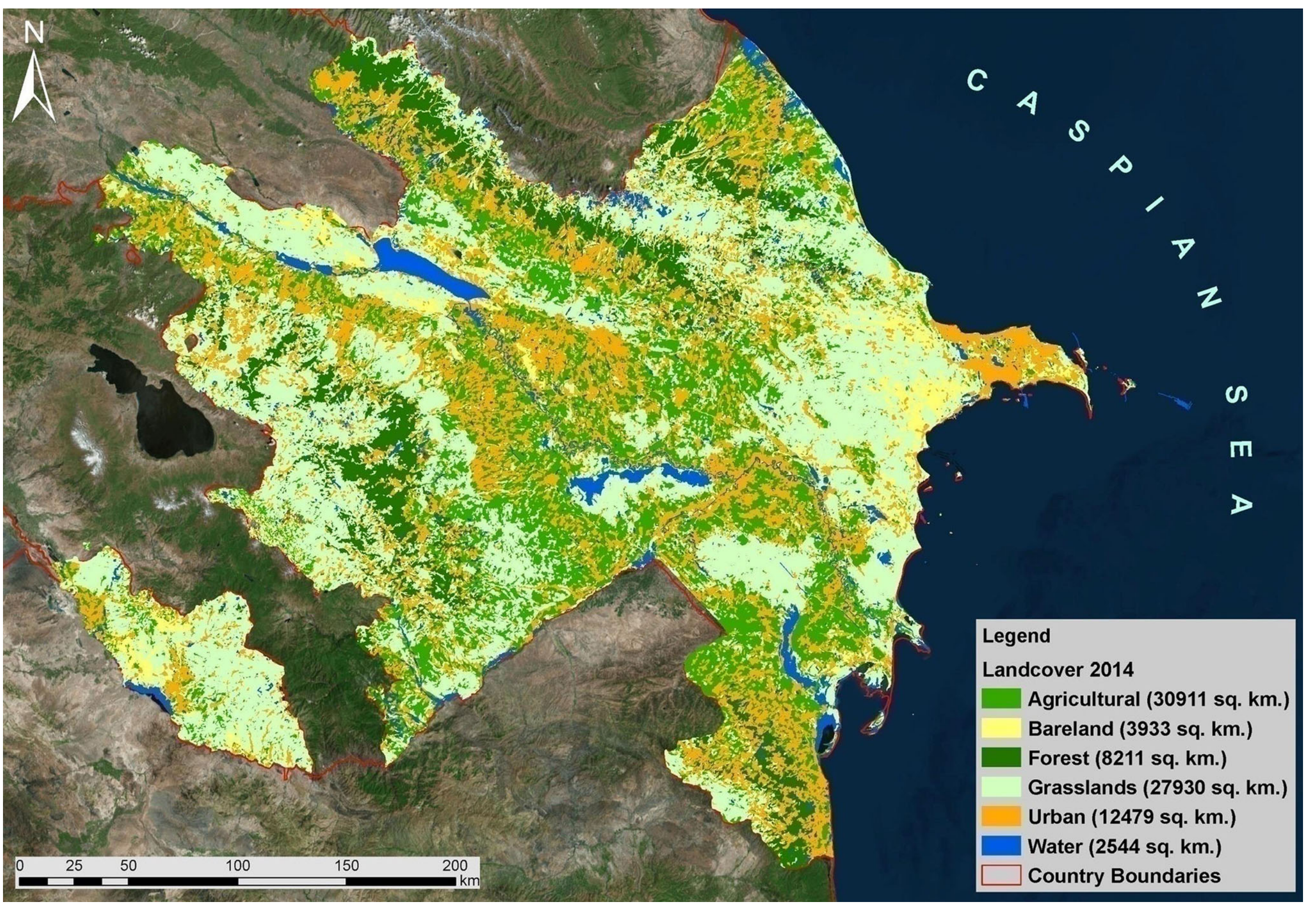


Fig. 4 Land-cover classes derived from LANDSAT 2014 satellite imagery

subtropic, temperate and frigid climates occur in the country. The average annual temperatures amount to 15 °C in the plains, while in high mountain regions they even reach negative values (Fig. 2c). In July temperatures reach 25–27 °C in Aran Region and 5 °C in the mountain regions.

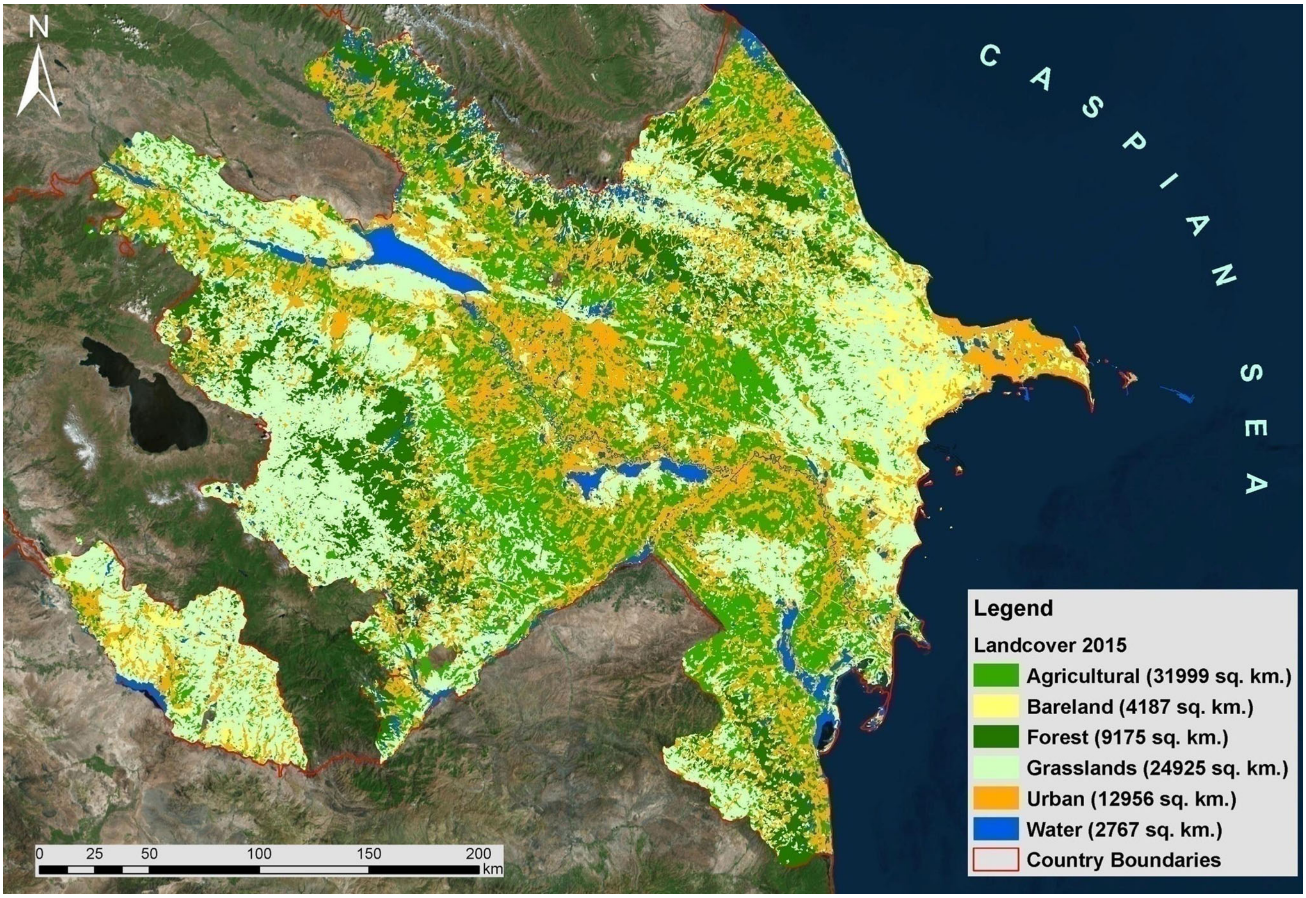


Fig. 5 Land-cover classes derived from LANDSAT 2015 satellite imagery

Table 1 Error (confusion/contingency) matrix of 2014 land-cover classification of LANDSAT-8 imagery

Landcover 2014	Agriculture	Bareland	Forest	Grassland	Builtup	Water	User's accuracy (%)
Agriculture	**80**	6	9	30	14	8	54
Bareland	1	**93**	0	1	0	3	95
Forest	0	0	**99**	1	0	0	99
Grassland	12	9	1	**73**	0	0	77
Built-up	16	1	0	5	**96**	2	80
Water	1	1	1	0	0	**97**	97
Producer's accuracy	73 %	85 %	90 %	66 %	87 %	88 %	82

Table 2 Error (confusion/contingency) matrix of 2015 land-cover classification of LANDSAT-8 imagery

Landcover 2015	Agriculture	Bareland	Forest	Grassland	Builtup	Water	User's accuracy (%)
Agriculture	**92**	1	1	26	10	2	70
Bareland	1	**98**	0	3	0	1	95
Forest	0	0	**108**	2	1	1	96
Grassland	6	6	0	**77**	0	2	85
Built-up	11	5	1	2	**98**	6	80
Water	0	0	0	0	1	**98**	99
Producer's accuracy	84 %	89 %	98 %	70 %	89 %	89 %	87

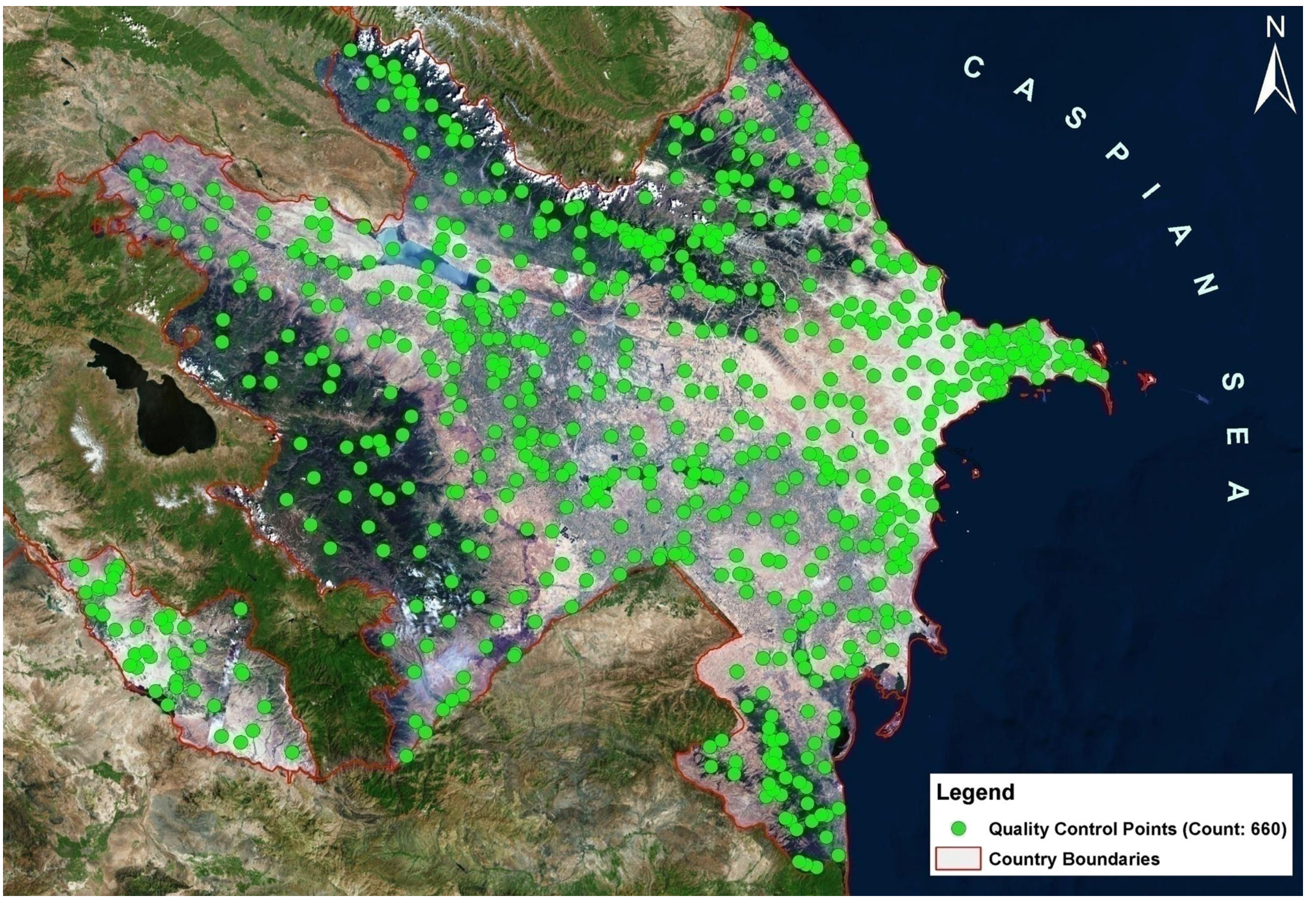


Fig. 6 Spatial distribution of quality-control samples of land-cover classes

Data processing

Segmentation, classification and validation of land-cover accuracy

LANDSAT-8 OLI (Operational Land Imager) satellite images collected during vegetation peak seasons of Azerbaijan (April–July) were used for the present study to derive land-cover maps of 2014 and 2015. LANDSAT-8 OLI provides a spatial resolution of 30 m, covering 185 km cross-track by 180 km along-track with a repetition rate of 16 days. Object-based segmentation and classification techniques were used to map following land-cover classes: agricultural land, bare soil, forest, grassland,

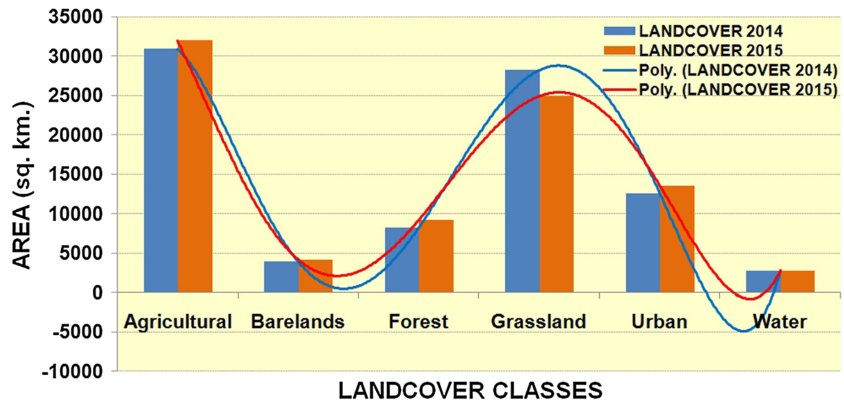


Fig. 7 Gross change of land-cover classes between 2014 and 2015

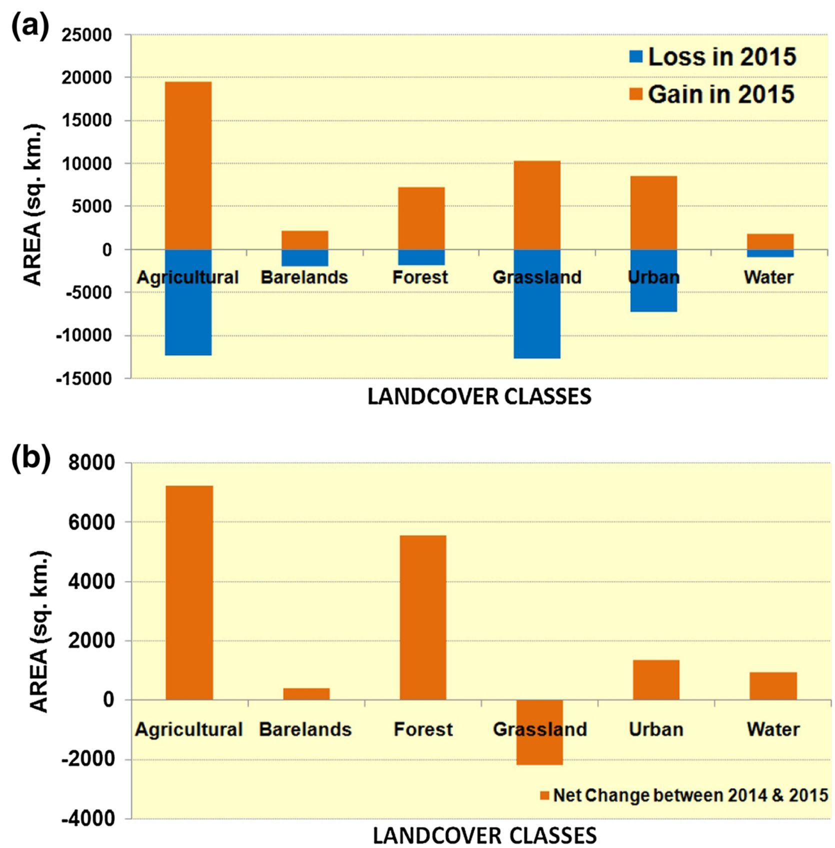


Fig. 8 **a** Loss and gains of land-cover classes between 2014 and 2015; **b** net change of land-cover classes between 2014 and 2015

built-up areas and water bodies. The object-based approach is based on the classification of the initially computed segmentation of satellite or airborne images. The segmentation process is based on the partitioning of the image into the segmented objects using the certainty criterion of homogeneity (Yan 2003). The multiresolution segmentation was used for the computation of image segmentation based on the neighbouring pixels with the same heterogeneity in both spectral and spatial domain. After the multiresolution segmentation, the 27,956 and 24,785 training samples were collected to run the nearest neighbour classification algorithm. Quality assurance of the classified land-cover was performed using randomly distributed 660 control points and the standard confusion matrix. The workflow for the object-based segmentation, classification, quality assurance and land-cover analysis is shown in Fig. 3.

Quantitative assessment of gross and net land-cover changes

Net land-cover changes should be considered for the quantification of actual transformations between land-cover classes. Previous studies by Fuchs et al. (2015) showed that the difference in estimated land changes between gross and net values could have significant consequences on the overall change quantity in land-cover. The gross change represents the overall rates of land-cover classes for different years, whereas it does not consider the spatiotemporal shifts between the land-cover classes and does not present the actual availability of specific land-cover classes. The gross change is computed based on the classified land-cover types, whereas the net change requires geospatial overlay-analysis for the computation of shifts within land-cover classes which provides the gains and losses for the various land-cover types. For the present research, both gross and net changes were calculated based on the land-cover classes derived from 2014 to 2015 LANDSAT satellite imagery.

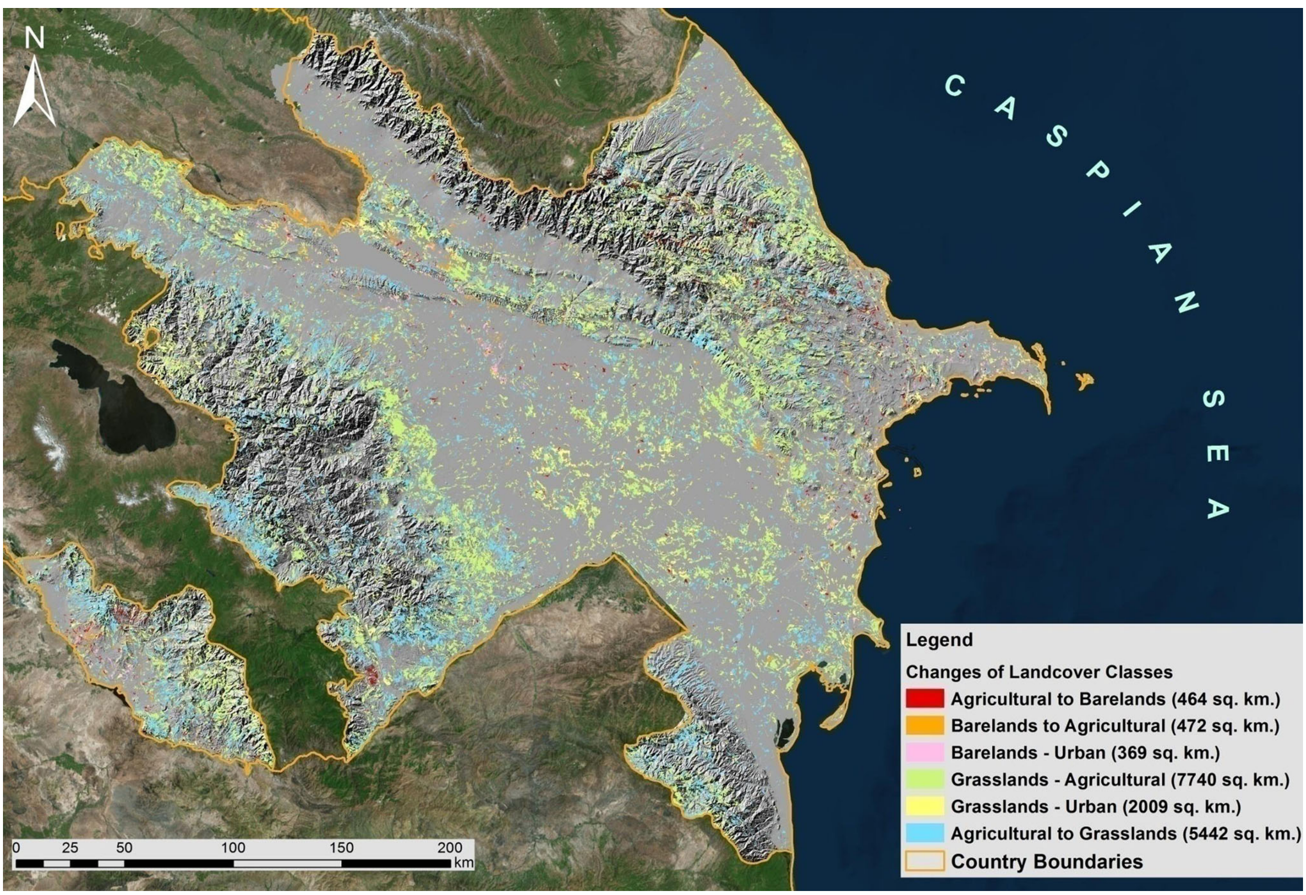


Fig. 9 Map of significant changes in land-cover classes between 2014 and 2015

Results

Produced land-cover and classification accuracy

The land-cover maps produced for 2014 and 2015 are presented in Figs. 4 and 5. The accuracy of the land-cover classification validated by means of 660 randomly distributed quality control points is presented in Tables 1 and 2. They show that the overall accuracies of the 2014 and 2015 land-cover maps were 82 and 87 % respectively. This implies that the achieved accuracies can be considered to be acceptable for further land-cover quantification and change detection analyses (Fig. 6).

Gross and net change detection analysis of land-cover classes

The gross change of land-cover classes representing the total areas modified between two periods is presented in Fig. 7. Between 2014 and 2015 an increase of the gross change areas of agricultural, forest and urban land-cover classes were observed. The area of agricultural land increased from 30,911 to 31,999 km^2. The built-up area increased from 12,550 to 13,548 km^2. The area of forest increased from 8211 to 9175 km. A decrease in area from 28,229 to 24,925 km^2 was observed for grassland. The areas with bare soil and water did not significantly change from 2014 to 2015. However, as can be see in Figs. 8a, b

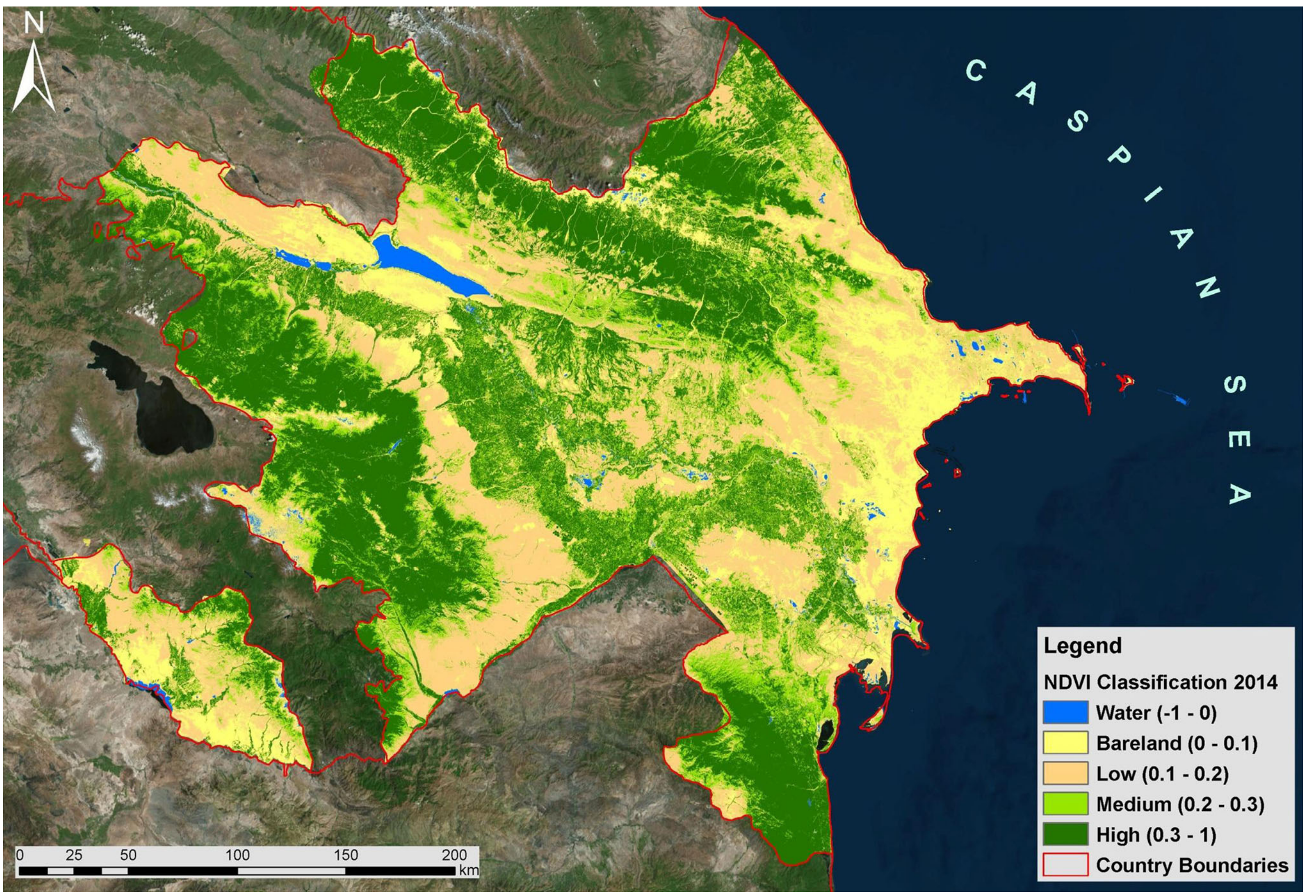


Fig. 10 Map of classified NDVI rates for 2014

the net change analysis revealed both gains and losses of these land-cover classes. This allowed to determine the positive net changes of 7229, 5576, 1337, 399, 951 km^2. For agricultural land, forest, built-up areas, bare soil and water bodies, correspondingly. A negative net change of 2198 km^2 was observed for grassland. This is due to the significant changes of grassland into agricultural land (Fig. 8b). Significant changes between 2014 and 2015 gross or net changes were not observed for the land-cover class of bare soil. A map showing the significant changes in land-cover classes between 2014 and 2015 is presented in Fig. 9.

Quantification of normalized difference vegetation indices for 2014 and 2015 land-cover

The classification of NDVIs derived from 2014 to 2015 LANDSAT-8 satellite images is presented in Figs. 10 and 11. Figure 12 a presents the vegetation cover of agricultural land increased in the low (0.1–0.2) and medium (0.2–0.3) and decreased in the high (0.3–1) NDVI values. Similar trends were observed for the built-up areas (Fig. 12b). A decrease in 2015 relative to 2014 in the NDVIs within grassland was observed for its low (0.1–0.2), medium (0.2–0.3) and high (0.3–1) values (Fig. 12c). The

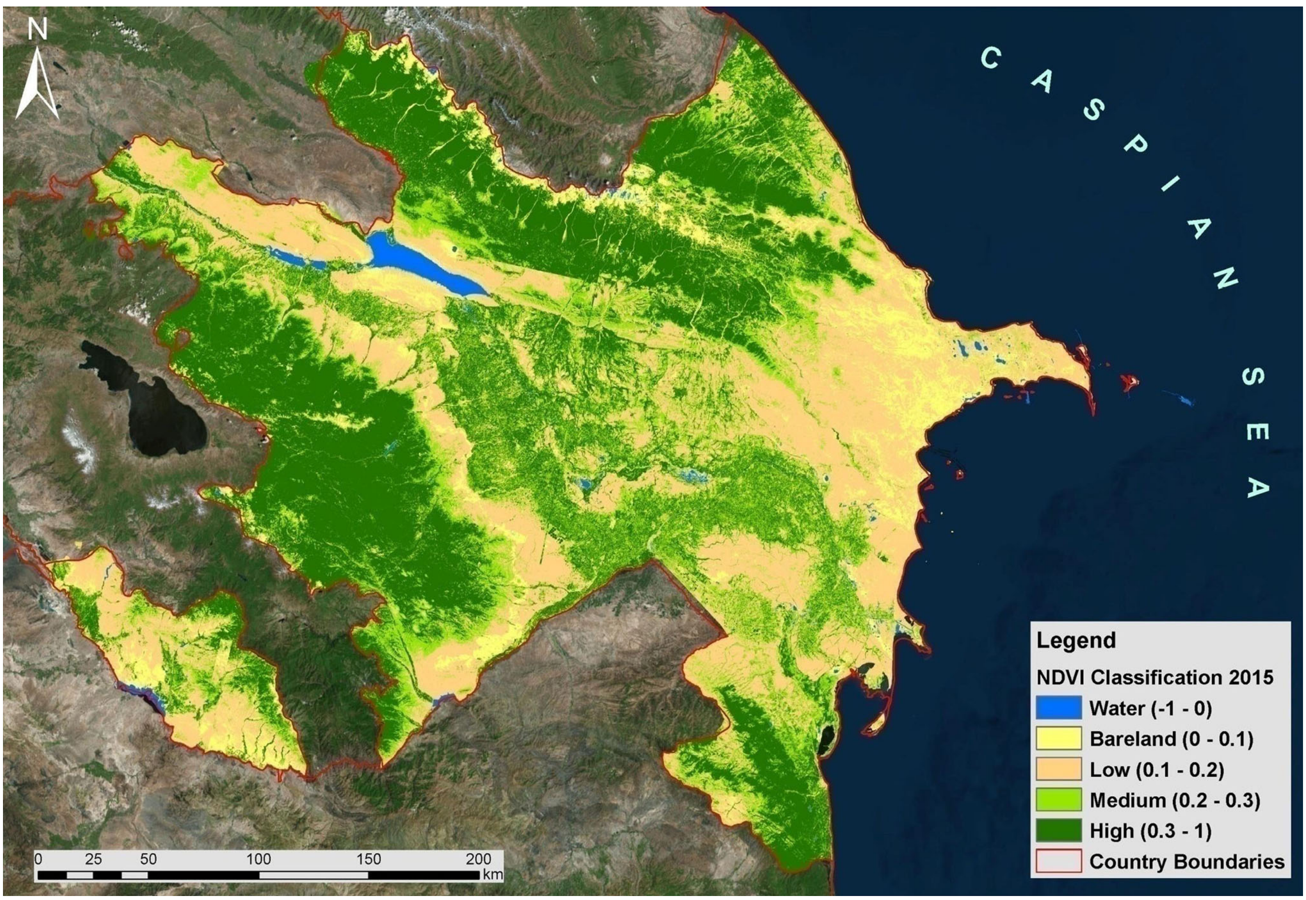


Fig. 11 Map of classified NDVI rates for 2015

area with high (0.3–1) NDVI values in the forest land-cover was higher in 2015 than in 2014 (Fig. 12d). The positive and negative NDVI changes between 2014 and 2015 are presented in Fig. 13a, b.

Conclusions

The achieved overall accuracies for the object-based land-cover classification for 2014 and 2015 were 82 and 87 %, respectively. They were considered sufficient for land-cover quantification and change detection analyses.

Between 2014 and 2015 an increase of the gross areal change of agricultural, forest and built-up areas was observed. The gross area of agricultural land increased from 30,911 to 31,999 km^2. The gross area of urban or built-up areas increased from 12,550 to 13,548 km^2. The gross area of forest increased from 8211 to 9175 km^2. A decrease was observed in the gross area of grassland, leading from 28,229 to 24,925 km^2. This was primarily related to the land-cover transformations driven by agricultural activities. The gross areas of bare soil and water bodies did not change significantly from 2014 to 2015.

Net change analysis, however, revealed significant differences in comparison to gross change areas for both gains and losses of the land-cover classes. The net change analysis revealed positive net changes of 7229, 5576, 1337, 399, 951 km^2 for agricultural land, forest, built-up areas, bare soil and water bodies, correspondingly. A negative net change of 2198 km^2 was observed for grassland. This allowed to conclude that the negative net change of grassland was related with the significant changes of grassland into agricultural land. No significant changes between 2014 and 2015 were observed for the land-cover class of bare soil.

The classification of NDVIs derived from 2014 to 2015 LANDSAT-8 satellite imagery showed that the vegetation cover of agricultural and built-up land increased for the low (0.1–0.2) and medium (0.2–0.3) and decreased for the high (0.3–1) NDVI values. The areas of high (0.3–1) NDVIs in forest were observed to be higher in 2015 than in 2014. For grassland, the low (0.1–0.2), medium (0.2–0.3) and high (0.3–1) NDVI values went down from 2014 to 2015. Also, for the high (0.3–1) NDVIs of agricultural land, build-up areas and grassland a reduction was observed. This is due to agricultural and industrial

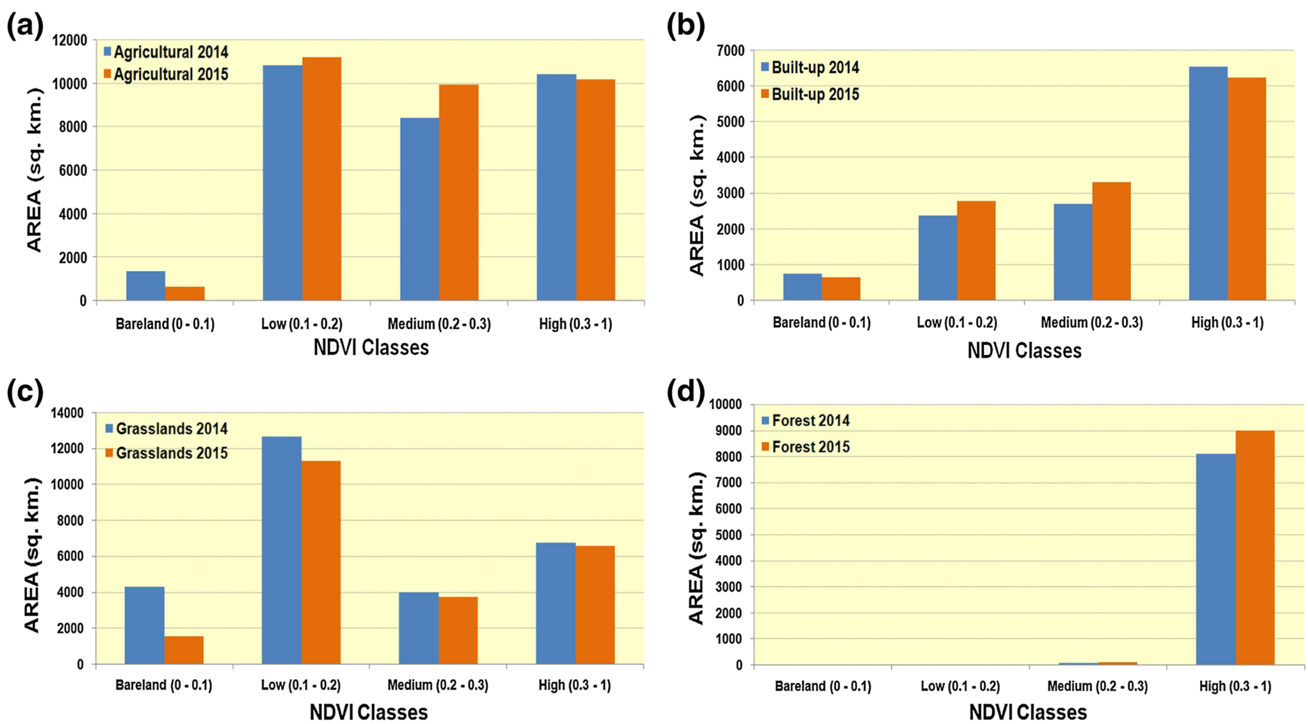
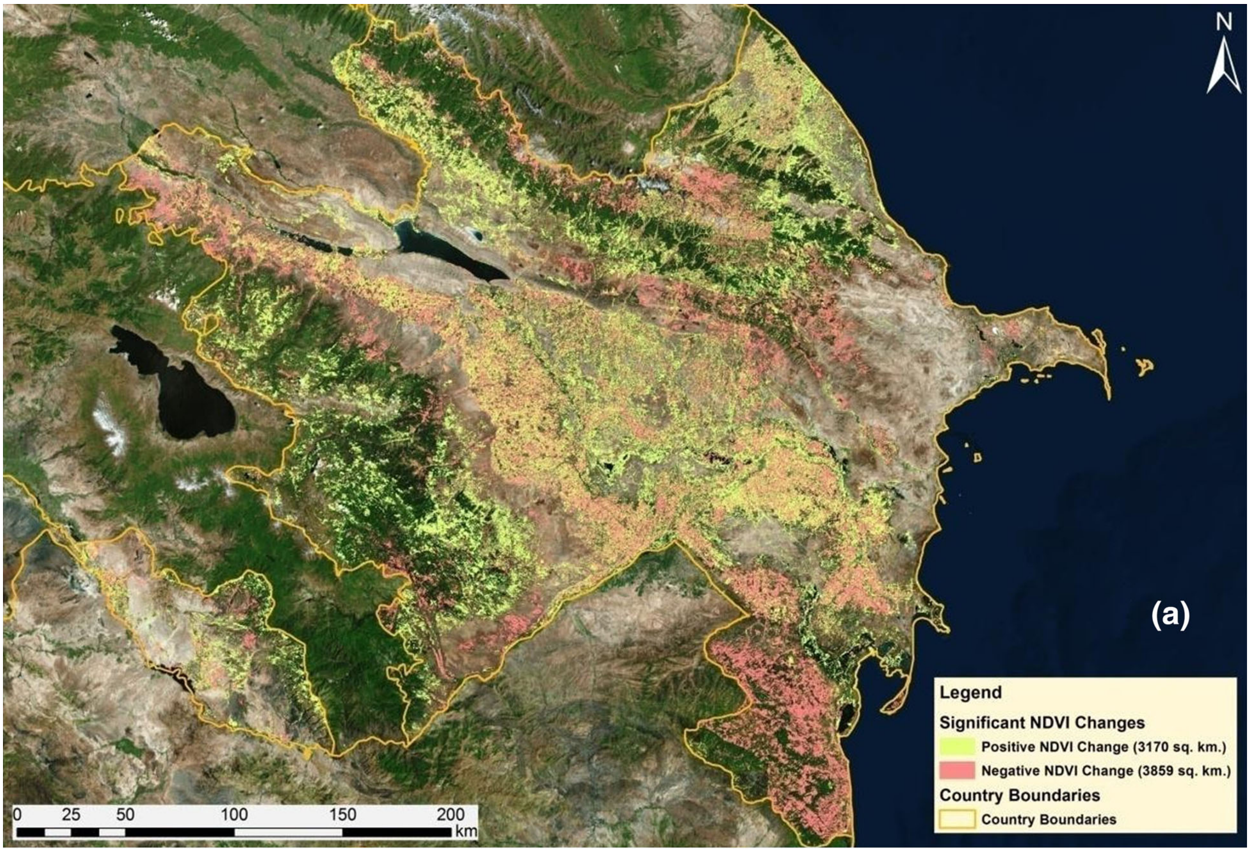


Fig. 12 Changes in NDVI between 2014 and 2015 for: **a** agricultural land; **b** built-up areas; **c** grassland; **d** forest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(a)
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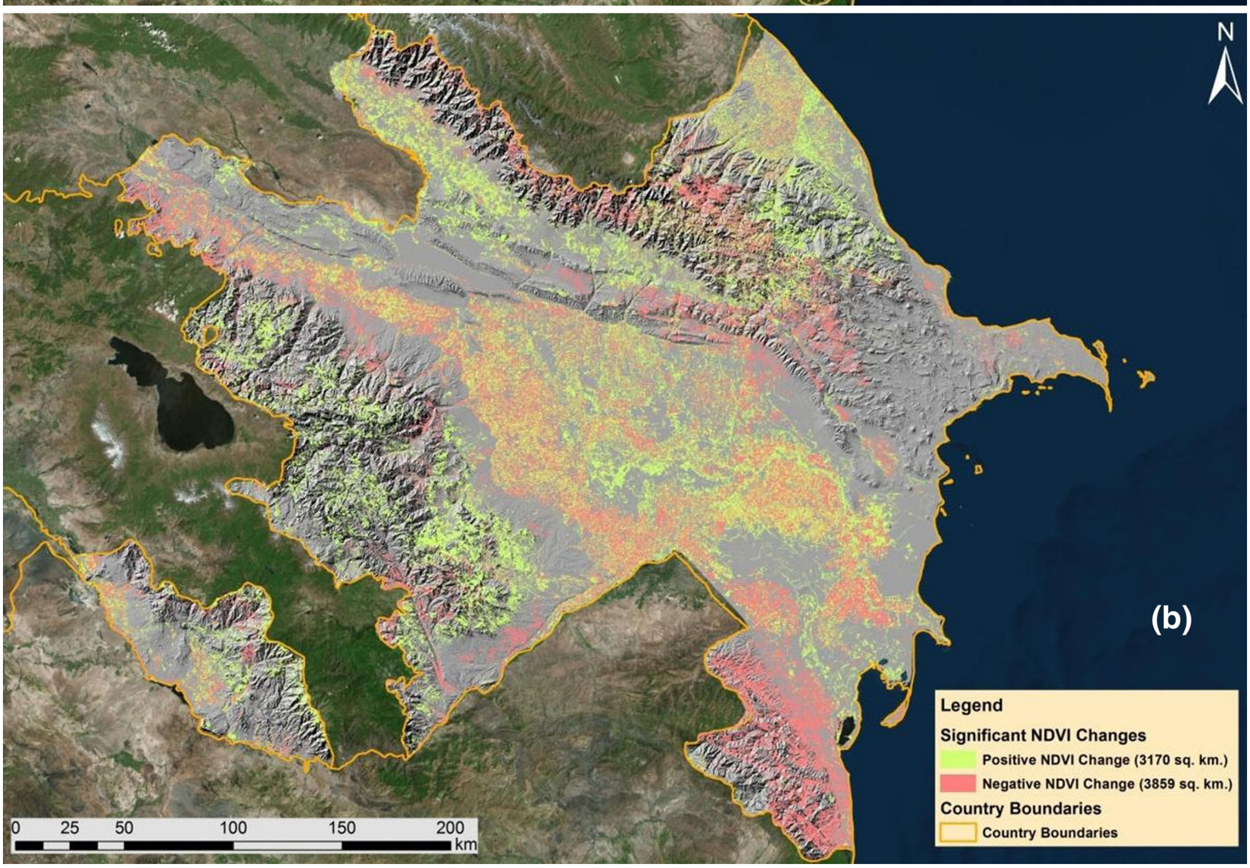
Significant NDVI Changes
Positive NDVI Change (3170 sq. km.)
Negative NDVI Change (3859 sq. km.)
Country Boundaries
Country Boundaries
0 25 50 100 150 200
km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Significant NDVI Changes
Positive NDVI Change (3170 sq. km.)
Negative NDVI Change (3859 sq. km.)
Country Boundaries
Country Boundaries
0 25 50 100 150 200
km

◀ **Fig. 13** Map of NDVI changes between 2014 and 2015: **a** background: satellite imagery; **b** background: hill-shaded relief

activities but may also be related to climate change impacts. For the entire terrain of Azerbaijan, the positive and negative NDVI changes were observed to be 3170–3859 km^2, respectively.

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