Land cover change in Tashkent province during 1992 – 2018

B Alikhanov¹, Sh Alikhanova¹, R Oymatov¹, Z Fayzullaev¹ and A Pulatov*¹

¹Tashkent Institute of Irrigation and Agricultural Mechanization Engineers, Tashkent, Uzbekistan

alimpulatov@mail.ru

Abstract. In this research, a specific period in time (from 1992 – 2018) with 8-10 years’ timescales of Landsat satellite images were used for land cover classification. To detect land cover change combined classification method with clustering study area into 120 classes and further validation by Google Earth was performed. Our findings show significant land cover changes during the whole study period. Especially this related to grassland/scrubland/meadow/agriculture class, which was around 7000 km² in 1992, and it dramatically fell to 3000 km² in 2008 and reached 6000 km² after ten years. Forest/parks/woodlands land cover class shows a tendency to increase and consisted of its maximum area 4000 km², but then rapidly fell to 1600 km² within the next ten years. Glaciers, in contrast, covered area of 1825 km², but then starts steadily decline and finally reaches only 263 km² in 2018. Bare soil and barren land starts from 3111 km² and expands to 5640 km² area in 2018. The same pattern shows urban/asphalt/rocks class started from 1089 km² and ends with 2677 km². Only water bodies do not represent any significant change in Tashkent province during the study period.

1. Introduction

Many challenges our planet is facing today and the scope of global changes will not reduce, but will only increase during the next decades. From various environmental challenges facing the earth, land-use and land-cover (LULC) changes are probably the most notable [7]. The process of land use and the land cover change affect many ecosystem functions and services (biodiversity, hydrology, climate, carbon cycle, soil fertility). LULC influences surface radiation balance, temperature, water flow, water permeability, and its spatial and temporal change is important for earth system modeling, global climate change, and sustainable development planning [1, 3, 12].

Though LULC refers to different terms of land use is the physical properties of land, land cover is the human use of land. LULC is the result of human-environment interaction [15, 16]. The United Nations System of Environmental Economic Accounting (UN-SEEA) defined the term of land cover classification as “observed physical and biological land cover of the Earth’s surface and includes natural vegetation and abiotic (non-living) surfaces” [19]. LULC has a mutual relationship with climate and it can be impacted by climate change and influenced to climate as feedback [6, 10].

Numerous researches show that human has altered approximately half of the ice-free land surface. The human population is predicted to increase by 50-100 according to different scenarios and thus will consequently lead to further pressure to land [7]. Land cover change plays a huge role in the carbon cycle which in turn regulates the concentration of the greenhouse gas in the atmosphere [7, 12].
LULC is affected by numerous factors. It is noticed, that in regions with high population density, high urbanization rate and industrialization LULC has a higher change detection degree [6, 20]. Such kind of changes modifies surface energy balance and alters the microclimate of the region.

With the development of technologies and science, new methods for research has evolved since 1970’s satellite remote sensing data provide the basis for constant monitoring over large territory [3]. Remote sensing provides periodic observations that are independent of governmental institutions and can be compared with them as free from bias and policy data [13].

According to several reports [14, 17], Central Asia is among the sub-regions most vulnerable to climate change. With a projected increase in annual average temperature, the region is likely to suffer even more from climate change impacts resulting in deterioration of the state of natural resources. The negative effects will be particularly significant on land resources and land cover. According to the recent [19], between 2000 and 2015 28% of the land was degraded in the Central and Southern Asia region, which is the second-highest degradation rate observed globally after Oceania. According to this Report, the observed net loss in global natural and semi-natural land cover classes was mostly of an anthropogenic cause that includes “desertification, deforestation, improper soil management, cropland expansion, and urbanization”. Also, there is a trend towards declining of the productivity of land cover classes, grasslands being the top “losers” among all.

According to the Food and Agriculture Organization of the United Nations [5] annual statistical data on land cover from 1992 to 2017, there is an increasing growth trend in the terrestrial barren land in Uzbekistan. All in all, there are 10 different land cover classes in the world are showed in Figure 1.

Various classification methods were used to research LULC in Uzbekistan. For example, [21] used Landsat and MODIS satellites images to research forest cover change in Central Asia for the years 2009-2011 [11] researched cropland area change in Kazakhstan from 1953 to 2010 using Landsat TM/ETM+ images using semi-automatic non-parametric support vector machines (SVM) [4] used classification trees to generate a phenological state of crops in Kashkadarya province, Uzbekistan, for the period 1972-2000 [9] applied supervised maximum likelihood classification method to Landsat satellite images to detect LULC change for Bostanlik province, Uzbekistan, for period 1989-2017.
The main objective of this research is to analyze the general land cover change in Tashkent Province during the period from 1989 to 2018.

2. Materials and methods

2.1 Study area

Tashkent Province is located in the North-Eastern part of Uzbekistan (Figure 2). According to the Koppen-Geiger climate classification system, Tashkent province is dominated by a hot-summer Mediterranean climate with annual precipitation constituting 300 mm. According to official data from 2019, the total area of the Province is 1525325 hectares. The relief of the province is uneven, ranging from mountain foothills in the East to plains in the West. The average temperature in January drops to –1°C, whereas the July average reaches +36°C. The main water source is the Charvak reservoir and the Syrdarya and Chirchik rivers [18].

![Figure 2. Study area of Tashkent province](https://example.com/figure2.jpg)

2.2 Remote sensing data analysis

For analysis of Tashkent Province Landsat, quadrats were downloaded from the Earth Explorer application, United States Geological Survey (USGS) website (https://earthdata.nasa.gov). Images were acquired specifically for late May, June, or July months, which have low cloud cover and peak of biomass rate. Finding the appropriate images of high quality for the study period for these months was one of the most challenging parts of the research. Not all images that we wanted to exist in the USGS database (especially concerning Landsat 5 TM), so it was decided to work with those that were available.

| Year | DOY | Sensor | Path/Row |
|------|-----|--------|----------|
|      |     |        |          |

Table 1. Landsat images from the Earth Explorer applied during the research
After the acquisition of Landsat Images for the study period and the study area, images were combined using the mosaic tool to cover the whole Tashkent province. For this, four Landsat image quadrats were combined into one image. Afterward, Tashkent province was used with Extract by Mask tool in ESRI ArcGIS software.

![Figure 3. Image 2000 after mosaic and after extraction of Tashkent province in false color [NIR-Red-Green]](image)

Before undertaking image classification, we decided to apply radiometric and atmospheric correction using ATCOR 2 to make the results of the classification reliable and comparable to each other. Radiometric correction converts first at-sensor digital numbers into radiance (watt per square meter) and then into the top of the atmosphere albedo for Landsat 5 TM using the following formulas:

\[
L_\lambda = \text{gain} \times DN + \text{bias}
\]

\[
p = \frac{\pi \times L_\lambda \times d^2}{\text{ESUN}_\lambda \cos \theta}
\]

Where: \( p \) is the unitless planetary reflectance of the object for the specific band; \( d \) is the distance between the Sun and the Earth on acquisition day (see Annex 1); \( \cos \theta \) is the cosine of solar zenith angle (solar zenith angle= 90 – solar elevation); \( \text{ESUN}_\lambda \) is the solar exoatmospheric irradiance for each specific band; \( L_\lambda \) is the radiance of pixel (watts/m² sterd).

For Landsat 8 radiometric and atmospheric correction differs from previous sensors due to some technical characteristics of Landsat 8 OLI/TIRS sensor device:

\[
p = \frac{2 \times 0.00001 \times DN - 0.1}{\cos \cos \theta}
\]
Solar exoatmospheric irradiance, solar distance, and sun elevation were taken from images containing USGS .mtl files.

Atmospheric correction is necessary to eliminate or reduce the impact of atmospheric gases (aerosols, dust, carbon dioxide, nitrogen oxide) for the electromagnetic spectrum, reflected from the surface. To perform this ATCOR 2 was applied. Clouds that are not possible to remove during atmospheric correction were eliminated during the post-classification correction.

![Figure 4. Before and after atmospheric correction in ATCOR](image)

For the classification method of multi-temporal satellite information, the decision to use a combined classification method, which involves unsupervised and supervised classification methods was made. The main advantage of combined classification is that it is more reliable and accurate compared to other classification methods. The main disadvantage – this method is time consuming. It included three steps: 1) Unsupervised classification (a division of the study area into 120 clusters); 2) Giving each cluster its color using the original image and Google Earth Pro; 3) Recode 120 classes into six final classes. After the classification manual, post-classification correction was applied to make classification more accurate and reliable and remove clouds and hill shadows.

Accuracy assessment of final maps was done in ERDAS IMAGINE accuracy assessment tool. For these 120 random samples, all across the study area were generated by the software and then manually checked by the authors. If the accuracy was less than 80%, we continued post-classification correction to improve the classification results until the desired level was reached. Besides the accuracy, the Kappa statistics (see below) of each image were estimated and presented in the Results part.

\[
\text{Kappa} = \frac{\text{observed accuracy} - \text{chance agreement}}{1 - \text{chance agreement}}
\]

Reclassifying and calculating areas, as well as change detection matrix and legend for final maps was performed in ArcGIS software. The results are represented in square kilometers. The study area is divided into six major: forest, grasslands, agriculture, water, glaciers, urban and bare soil.

3. Results and discussions

Accuracy assessment was done using the Accuracy assessment tool in ERDAS Imagine. We decided to use random sampling with 120 points all over the study area to validate the output of classified images to the audience. The output map was compared with Google Earth's up-to-date images with higher spatial resolution. In the case of the absence of an image, the original Landsat satellite image was used for validation.
Checking each sample point and comparing it with classified pixel were time consuming. Overall, 480 sample points were verified for all temporal data. In case if the classification accuracy was less than 80%, further post-classification correction was performed (see Table 2).

| Year       | Accuracy | Kappa statistics |
|------------|----------|------------------|
| 1989/1992  | 82%      | 0.76             |
| 2000       | 89%      | 0.85             |
| 2008       | 86%      | 0.81             |
| 2018       | 87%      | 0.83             |

As can be seen from Table 2, the year 2000 shows the highest accuracy. It should be mentioned that all four quadrats, that was used during mosaic for this year have high quality data. The difference between paths 153 and 154 equaled to 1 month. All four images contained very small cloud cover (see Figure 2), which also influenced the final result.
Figure 6. Land use and land cover in 2000 in Tashkent province

Figure 7. Land use and land cover in 2008 in Tashkent province
Figure 8. Land use and land cover in 2018 in Tashkent province and Tashkent city

The smallest classification accuracy was with years from 1989 to 1992. The reason behind this is that we could not find high quality images for all quadrats for years from 1989 to 1992, so we decided to mosaic two for each year captured by Landsat 5 TM in May, June, and July months. This resulted in a sharply changing land surface on the edges of quadrats. In addition to this, these years do not always have high spatial resolution reference images for validation, because such satellites like Quick Bird were launched later.

Figure 9. Land covers change in the study area from 1989 to 2018
Figure 9 visually represents the general land cover and land use change from 1989 to 2018 across the whole Tashkent Province. The vertical axis is expressed in square kilometers, while the horizontal axis shows classified years. We divided the study area into 6 general classes.

All land cover and land use classes sharply fluctuate during the research period except for water. Especially this concerns grasslands/agriculture/scrubland/meadow areas and forest/park/woodland class. Nevertheless, the trend and outcome of fluctuations are different. If grasslands/agriculture/scrubland/meadow covered most of Tashkent province (more than 7000 square kilometers) in 1989 and 1990, after independence (starting from 1991) it sharply declined and consisted two times less for 2000 (-24 %) and even less in 2008 (-4 % from the total area). However, the next decade marked significant growth in grasslands/agriculture/scrubland/meadow area (+21 %). Yet, it is still 7 % less compared to 1989/1992. Such an overall trend of land cover can be due to multiple reasons: 1) Vegetation period shifted for the later period due to average daily and annual temperature decline compared to 2000-2008; 2) Government induced strict laws against unsustainable grazing of pastures; 3) Average annual daily and year precipitation increased during the following decade; 4) Aboveground biomass reduced in a forest and woodland areas and where it was mostly represented by shrubs and forbs; 5) Glaciers melting intensified from 2008 to 2018 (see Figure 9) and remaining land cover was invaded by herbs, grasses, and forbs; 6) Harvested agricultural areas were used for planting crops again during the research period.

Forest/woodland/parkland cover class first tended to increase from 1989/1992 up until 2008 (+13%). If at the beginning of the independence era, total forest areas made up nearly 2000 square kilometers, in after 16 years trees covered 4000 square kilometers. However, the next decade signalized a sharp decline of this class by -16 % (1600 square kilometers). Several factors lie behind this: 1) In the 2000’s government started to implement strict bans against cutting of trees, which was used by the local population as fuel wood, in the study area, 2) During the period from 2008 to 2018 there was uncontrolled/illegal cutting of trees and destroying of parks in Tashkent city resulting in general tree decline in the city and Tashkent province in general, followed by heavy public criticism; 3) Some agricultural areas during the peak of biomass could be classified as forest or woodlands because they have the similar reflectance in NIR spectrum.

Bare soil area, as well as an urban area, shows a rising trend during the study period in Tashkent province. Bare soil shows a sharp rise from 1989/1992 to 2000 (+18% from the total area). The next 8 years do not show any changes. Period 2008-2018 is followed by a slight decline in bare soil area and made up 5000 square kilometers. Urban/roads/ashphalt/minerals/ rocks total area logically growth during the next decades but then followed by a slight decline during 2008-2018. This can be due to grassland expansion covered rocks land cover.

Foremost, one of the most was challenging and time consuming parts of remote sensing analysis was data acquisition. The preliminary aim was to find and download data for May for each study year. The reason behind this is that May is perfect for two reasons: vegetation in forests and grasslands reaches its peak biomass and most of the agricultural crops in the region are not harvested yet. Moreover, the intensive grazing period only starts at the end of spring so the pastures contain their major aboveground biomass. However, finding images for all four quadrats for May month was hard due to many reasons: 1) some images for a certain row (153 or 154) did not exist in Earth Explorer database; 2) many images (quadrats) for the study region was low quality or contained a high percentage of cloud cover. In this case, images for the next month was downloaded and researched if they satisfied the quality needs. Nevertheless, this leads to one hindrance during and after classification – June and July months is the period of harvesting of most agricultural crops and intensive grazing period. Moreover, due to extreme heat days on these months and lack of precipitation, plants start losing their chlorophyll content and green color. Hence, the area of grasslands, agriculture, and meadow significantly reduce, and bare soil land cover significantly increases compared to the spring period.
The post-classification correction was important because no classification technique gave sufficient accuracy. The manual correction was important but required significant time and concentration. Many hill shades were classified as water during unsupervised classification by virtue of their similar signature—no reflectance at all spectral ranges. Clouds and their shadows also needed manual correction. For this purpose, Google Earth’s high spatial resolution images were used for validation. Nevertheless, not all images for the particular Landsat DOY or event month existed. In this case, we assigned the class value of the nearest pixels instead of the cloud and shadow.

Initially, we planned to start the classification period from 1991 or 1992. However, this intention faced significant troubles during the image search. Not all four quadrats (153/31, 153/32, 154/31, 154/32) for 1991 or 1992 had sufficient quality or were absent at all. Finally, we decided to mosaic images for the years 1989 (May month) and 1992 (July and June). This is the reason why the final map does not look uniformly and pixels sharply pass on the edge of each quadrat. This image also has the lowest accuracy level compared to others.

Another important note that should be mentioned in this chapter is the differentiation between bare soil and urban land cover classes. These two classes have very close signatures and sometimes it was very hard and time consuming to separate them manually. Harvested agriculture often also was classified as urban especially if there was some moisture content in the soil. In Tashkent city, the reflectance of trees merged with asphalt reflection and sometimes gave bare soil reflection or grassland. Differentiation of these two classes is crucial and should be a topic for separate research.

4. Conclusion
To recapitulate, land cover/land class change in Tashkent province shows significant fluctuations during the 1992–2018 periods. Highest fluctuation curvature displays grasslands/scrubland/agriculture/meadows land cover/class.

Glaciers’ land cover on top of the high mountains steadily reduced its area, starting from nearly 2000 km² at the beginning of the study period and ending by 287 km². This can be due to two major reasons: 1) images, that were acquired for 1989/1992 are for months, when glaciers only start melting (May-June), while other research years images are lose their significant area; 2) climate change (rise of temperature and decline of precipitation) impacts mountain glaciers, which start to misplace their area.

Urban areas, merged with rocks and minerals because they have a similar signature, generally increase for almost 1000 km². This is because of rapid urbanization in Tashkent city, as well as cutting trees and destroying city parks in the capital.

Bare soil area dramatically rises from 1992 to 2000 from 2700 km² to 5600 km² and then stabilizes during the next two decades. This is foremost can be related to a sharp decline of grasslands and agricultural areas in the same period. At the same time, water bodies remain unchanged during the whole study period.

Acknowledgments
The authors gratefully acknowledge Erasmus Mundus Action 2 projects TIMUR for supporting the first author with the scholarship award to pursue his MS research at Tashkent Institute of Irrigation and Agricultural Mechanization Engineers (Uzbekistan) and at Wageningen University, the Netherlands under double degree master programs, and personally, Ewa Wietsma, international project manager of Wageningen University, for moral support during his MS research. The authors also gratefully acknowledge joint TIIAME and WUR EcoGIS center and their staff for constant support during our research.
References
[1] Avila F B, Pitman A J, Donat M G, Alexander L V and Abramowitz G 2012 Climate model simulated changes in temperature extremes due to land cover change CHANGES IN CLIMATE EXTREMES DUE TO LULCC J. Geophys. Res. 117, n/a-n/a. DOI: 10.1029/2011JD016382
[2] 2014 Central Asian Pledge Action on Climate Change
[3] Chang Y, Hou K, Li X, Zhang Y, Chen P 2018 Review of Land Use and Land Cover Change research progress IOP Conf. Ser.: Earth Environ. Sci DOI:10.1088/17551315/113/1/012087
[4] Edlinger J, Conrad C, Lamers J, Khasankhanova G and Koellner T 2012 Reconstructing the Spatio-Temporal Development of Irrigation Systems in Uzbekistan Using Landsat Time Series 4 pp 3972–3994. DOI: 10.3390/rs4123972
[5] 2019 FAOSTAT: Land cover
[6] Gogoi P P, Vinoj V, Swain D, Roberts G, Dash J and Tripathy S 2019 Land use and land cover change effect on surface temperature over Eastern India. Sci Rep 9 p 8859. DOI: 10.1038/s41598-019-45213-z
[7] John F, Mustard Ruth S, Defries Tom Fisher and Emilio Moran 2004 LAND USE AND LAND COVER CHANGE PATHWAYS AND IMPACTS Land Change Science: Observing, Monitoring, and Understanding Trajectories of Change on Earth’s Surface Kluwier Netherlands Springe.
[8] John Latham, Renato Cumani, Ilaria Rosati, Mario Bloise 2014 Global Land Cover SHARE database Beta-Release Version 1 FAO, Rome Italy
[9] Juliev M, Pulatov A, Fuchs S, Hübl J 2019 Analysis of Land Use Land Cover Change Detection of Bostanlik District Pol. J. Environ. Stud 28 pp 3235–3242. DOI: 10.15244/pjoes/94216
[10] Kayet N, Pathak K, Chakrabarty A, Sahoo S 2016 Spatial impact of land use land cover change on surface temperature distribution in Saranda Forest Jharkhand. Model. Earth Syst. Environ 2(127). DOI: 10.1007/s40808-016-0159-x
[11] Kraemer R, Prishchepov A V, Müller D, Kueenmerle, 2015 Long-term agricultural land-cover change and potential for cropland expansion in the former Virgin Lands area of Kazakhstan Environ. Res. Lett. 10, 054012 DOI: 10.1088/1748-9326/10/5/054012
[12] Mahmood R, Pielke R A, Hubbard K G, Land cover changes and their biogeophysical effects on climate: LAND COVER CHANGES AND THEIR BIOGEOPHYSICAL EFFECTS ON CLIMATE Int. J. Climatol 2014 34, 929–953. DOI: 10.1002/joc.3736
[13] Potapov P, Turubanova S, Hansen M C 2011 Regional-scale boreal forest cover and change mapping using Landsat data composites for European Russia Remote Sensing of Environment 115 pp 548–561, 2011. DOI: 0.1016/j.rse.2010.10.001
[14] Saparov A, Bekenov M, Sanginov S 2009 Research Prospectus: A Vision for Sustainable Land Management Research in Central Asia
[15] Rawat, J S and Kumar M 2015 Monitoring land use/cover change using remote sensing and GIS techniques A case study of Hawalbagh block, district Almora, Uttarakhand, India. The Egyptian Journal of Remote Sensing and Space Science 18 pp 77–84. 2015. DOI: 10.1016/j.ejrs,
[16] Snyder P K, Delire C, Foley J A 2004 Evaluating the influence of different vegetation biomes on the global climate Climate Dynamics 23 pp 279–302 DOI: 10.1007/s00382-004-0430-0
[17] The World Bank 2014 Central Asian Countries Pledge Action on Climate Change. 2014
[18] 2019 Uzbekistan, Tashkent province. Retrieved from https://www.uzbektravel.com/eng/admin-div-tashkent.htm
[19] 2019 Sustainable development goals report
[20] Yang X, Hou Y and Chen B 2011 Observed surface warming induced by urbanization in east China D14113. DOI: 10.1029/2010JD015452
[21] Yin H, Khamzina A, Pflugmacher D and Martius C 2017 Forest cover mapping in post-Soviet Central Asia using multi-resolution remote sensing imagery Sci Rep 7 1375 DOI: 10.1038/s41598-017-01582-x