The driving forces of changes in land use of a Peri-urban area: the case of Tselinograd district, Kazakhstan

O Alipbeki[1*], *Ch* Alipbekova[1], *G* Mussaif[1], *N* Mineyev[1], *M* Aliyev[1], *B* Akhmetov[1], and *R* Turegeldiyeva[2]

[1]S Seifullin Kazakh Agro Technical University, Jhenis avenue, 62, 010011 Nur-Sultan, Kazakhstan
[2]M H Dulaty Taraz regional university, Suleimenova street, 7, 080012 Taraz, Kazakhstan

Abstract. This study focuses on the spatiotemporal dynamics of land use and land cover (LULC) in the Tselinograd district, which is a peri-urban area (PUA) of the metropolis Nur-Sultan. The analysis of LULC dynamics in PUA was carried out based on a supervised classification in the twenty-year interval (1998, 2008, and 2018). During the study period, noticeable changes occurred in the structure of LULC. At the border with the city, the built-up area increased dramatically. In the PUA the area of arable land and forests has grown steadily and pasture land has been declining. That is, there is an intensification of land use due to an increase in the share of arable land in the study area. The main drivers of LULC change in PUA are urban expansion and population growth of the Nur Sultan metropolis. In general, as a result of reasonable economic and legislative measures, the influence of the Urban sprawl of the capital of Kazakhstan on the PUA is still accompanied by a slight effect on its sustainable development. Our approach by using Geo-Information Techniques is useful for the rapid detection of phenomena and processes that can lead to the unstable development of PUA.

Keywords: land use, land cover; geo-information techniques, change detection, driving forces, Tselinograd district.

1 Introduction

Urban sprawl often challenges the sustainable development of PUA [1]. One of the main drivers of this process is the growth of the city population and the associated expansion of PUA lands or changes in land use intensity [2-4]. As a rule, the study of changes in the PUA is mainly carried out by assessing changes in LULC using Geo-Information Techniques (GIT) [5-7]. Therefore, instrumental systems for tracking the development of LULC using GIT [8] are being created. In recent years, special attention has been paid to the influence of Urban Sprawl on the LULC structure in PUA, as evidenced by an increase in the number of scientific studies in this direction [9].

Land use and land cover are two different terms that are usually evaluated in combination since the former (physical properties of surface elements) and the latter

* Corresponding author: oalipbekil@mail.ru

(human use of land cover) cannot be considered independent of each other [10]. Thus, LULC is the result of human interaction with the environment, which is affected by changes in socio-economic processes. By assessing changes in the long-term structure of LULC and by focusing on the main processes, it is possible to determine the drivers of these phenomena and take effective measures for the sustainable development of the Area of Interest (AOI) [11,12].

Of considerable interest is the assessment of the impact of the capital of Kazakhstan - the city of Nur-Sultan (former Tselinograd, Akmola, Astana) on the PUA, since over the past 20 years (1998–2018), it has turned from a provincial city into a large metropolis and has become a political, economic and cultural center of the republics [13]. It is only natural that the most promising method for assessing the impact of a metropolis is to study long-term changes in LULCs in PUAs using GIT.

In Kazakhstan, intensive land use studies using GIT were started in the 1990s [14-19]. In the initial stages, these studies were mainly aimed at preliminary assessments of damage from ineffective land use during the Soviet era, which led to serious environmental consequences, for example, the Aral Sea, the former Semipalatinsk nuclear test site, the Baikonur cosmodrome, and the development of minerals and hydrocarbons, etc. [14-23].

There are currently studies underway using GIT to study long-term changes in LULC in individual regions of the country. These works are devoted to the study of land-use changes outside the direct influence of urban sprawl [24-27]. At the same time, a comprehensive assessment of the impact of large cities of Kazakhstan on the surrounding agricultural areas using long-term spatiotemporal data series remains open for determining sustainable development approaches for both cities and PUAs.

Therefore, our main goal was to identify drivers that affect LULC change in the Tselinograd district, which borders the Nur-Sultan metropolis. The objectives of the study were to evaluate the changes in LULC in the AOI based on the use of 20-year-old RS data (1998, 2008, 2018), as well as assess the degree and consequences of the influence of these drivers on the sustainable development of this PUA.

2 Materials and methods

2.1 Study Area

The research area selected was the Tselinograd district, Akmola oblast, which surrounds the capital of the Republic of Kazakhstan, the city of Nur-Sultan. Previously, Nur-Sultan was called Tselinograd, Akmola, and Astana and now this metropolis AOI divides into two parts (Figure 1). The digital elevation model is based on the Shuttle Radar Topography Mission (SRTM) data [28].

The study area is located within the Kazakh Uplands, with low mountainous relief transition to a slightly wavy plain. The climate of the study area is continental and is part of the dry steppe zone. Winters are cold and lengthy, with an average temperature of −17-18°C in January; summers are moderately warm, with an average temperature of 20 °C in July. The average annual rainfall is 300–350 mm. Seven rivers flow through the district. Most of the small river tributaries dry up in the summer. There are many large and small lakes, the water mirrors of which are subject to seasonal changes. Tselinograd district is one of the main agricultural regions of the Akmola region. The main agricultural activity of the district is grain production. The railroads Nur-Sultan - Karaganda, and Nur-Sultan - Pavlodar pass through the territory of the AOI. Well-developed road network. According to official figures, the Tselinograd district covers an area of 7.8 thousand km2 and has 18 settlements [29-30].

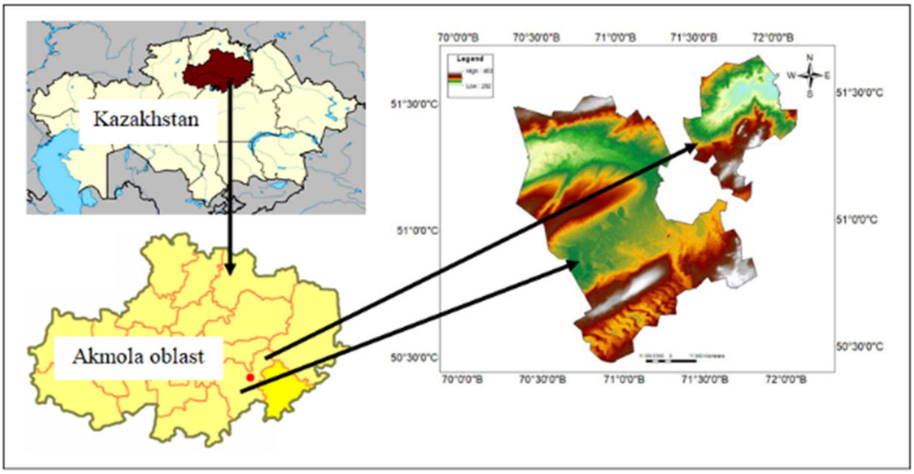

Fig. 1. Location and digital elevation map of the study area.

2.2 Data

Landsat 5 and 8 multispectral data obtained from the United States Geological Survey website [31] were used to study changes in LULC in the AOI. The main reason for using Landsat images is the availability of Earth observation data for a long period - from the mid-seventies of the last century and its sufficiently high spatial resolution (30 m) [32]. That is, Landsat is ideal for LULC analysis from 1998 to 2018. For example, the same free Sentinel-2 data for the territory of Kazakhstan is available only since the mid-twenties of our century [33]. Landsat images, geometrically corrected to UTM (Universal Transverse Mercator), zone 42 to the north, and WGS-1984 (World Geodetic System), were used. As shown in Table 1, each satellite dataset has information about four spectral bands that correspond to blue (B—blue), green (G-green), red (R—red), and near-infrared (near-infrared—NIR).

Table 1. Satellite images and their characteristics

Satellite	Sensor	Year/ Month/\Day	Metadata	No. of Bands	Spectral Composition	Wavelength (µm)
Landsat 5	TM	1998/09/17 1998/09/17 1998/09/24 1998/09/24	LT51540241998260BIK00 LT51540251998260BIK00 LT51550241998267BIK00 LT51550251998267BIK00	1 2 3 4	Visible Blue Visible Green Visible Red NIR	0.45-0.52 0.52-0.60 0.63-0.69 0.76-0.90
Landsat 5	TM	2008/04/12 2008/04/12 2008/05/05 2008/06/08 2008/07/26	LT51540242008208KHC01 LT51540252008160KHC01 LT51550242008103BJC01 LT51550252008103BJC01 LT51560242008126KHC01	1 2 3 4	Visible Blue Visible Green Visible Red NIR	0.45-0.52 0.52-0.60 0.63-0.69 0.76-0.90
Landsat 8	OLI	2018/08/14 2018/08/14	LC81550242018226LGN00 LC81550252018226LGN00	2 3 4 5	Blue Green Red NIR	0.45-0.51 0.53-0.59 0.63-0.67 0.85-0.88

We used the false color composite (FCC), consisting of the four channels B, G, R, and NIR, received from the Landsat 5 and 8 satellites, as well as color-balanced mosaics based on them from two unclouded images that cut along the border of the district. Images were used to identify and classify agricultural land and built-up areas in the study area in the multi-time period of 1998, 2008, and 2018.

To compile basic maps and interpret RS data, thematic maps were used by the Automated Information System of the State Land Cadastre [34]. Based on them, geodatabases were compiled. The geodatabase was used to collect training samples, ground-truthing, evaluate the accuracy of the classification and determine the real ownership of land.

2.3 Methods for classifying and accuracy assessment

For the first level of classification, the following five LULC classes were used according to CORINE [33], as seen in Table 2: arable land, pastures, water, forest, and built-up areas.

Table 2. Land use and land cover classes of the study area.

Level 1	Level 2
Arable land	Wheat, barley, sunflower, alfalfa, a different type of fallows
Pasture	Pastures, meadows, haymaking, deposits,
Water	Lakes, reservoirs, rivers
Forest	Deciduous, coniferous, mixed, forest nurseries, forest plantations
Built-up area	Settlements, industrial zone

We used the supervised classification of the LULC, the task of which was to detect objects of already known types in the images, which required some preliminary knowledge about the studied area of the Earth's surface. The maximum likelihood classifier (ML) was used for the supervised classification in this particular study. The ML classifier is one of the most widely used, extremely simple, and easily implemented algorithms. Moreover, ML is very well known and has already been successfully applied to a broad range of remote sensing problems [36,37]. Therefore, in this particular study, supervised classification was conducted using the image processing software ArcGIS (version 10.6.1) for LULC classification [38]. After initial supervised classification, the LULC map was edited based on ground verification of doubtful areas, and some classes were recoded into their respective classes. Ground truthing/verification was done on those particular areas that were not clear in the classification. In this process, land use and land cover maps were prepared initially, and the confusing spots were identified. For each class, i.e., arable land, pastures, water, forest, and built-up areas, at least twelve points were marked. An exhaustive ground-truthing of the study area was carried out, and some corrections were subsequently made. The ground reference data used for the image classification were further applied for accuracy assessment.

After ground-truthing, an accuracy assessment was carried out, which is the most important way to assess the reliability of a map. No image classification is said to be complete unless its accuracy has been assessed. To determine the accuracy of classification, a sample of pixels was selected on the classified image, and their class identities were compared with the ground reference data. In this study, the classification error matrix (or confusing matrix) was used, which is a common means of expressing classification accuracy. In the error matrix, the overall classification confidence indicator is defined as the number of correctly classified points located along the diagonal of the table (in %). This number may be random. To take this fact into account when summarizing the results, the so-called coefficient or K (Kappa) index, which corrects for randomness, is often used.

Kappa analysis is a discrete multivariate technique that calculates the producer's and user's overall accuracy as well as the Kappa accuracy level.

The Kappa index is calculated by the following formula [39]:

$$K = (d-q)/(N-q) \quad (1)$$

where d is the number of cases where the result is obtained correctly (the sum of the values on the diagonal of the error matrix); q is the number of random results calculated in terms of the number of random results in rows nc and true results in columns nr of the correspondence matrix, calculated as

$$q = \sum nc\ nr/N \quad (2)$$

where N is the total number of points.

For absolutely accurate results (all N points on the diagonal), Kappa is 1, and for a purely random hit, Kappa is 0.

After accuracy assessment and correction, the class-wise areas of 1998, 2008, and 2018 mosaics were calculated. In LULC classification, change detection is a very important process, which was done after the completion of the calculation and analysis of the land use land cover classes from the 1998, 2008, and 2018 mosaics. By using the change detection option in ArcGIS software, the differences between the three mosaics of the Tselinograd district for all five LULC classes were computed. The integral structure of the methodological approach that we used is shown in the block diagram in Figure 2.

Thus, the methodological approaches we used to classify LULC and evaluate its accuracy were repeatedly tested and found reliable enough to be able to automate these processes.

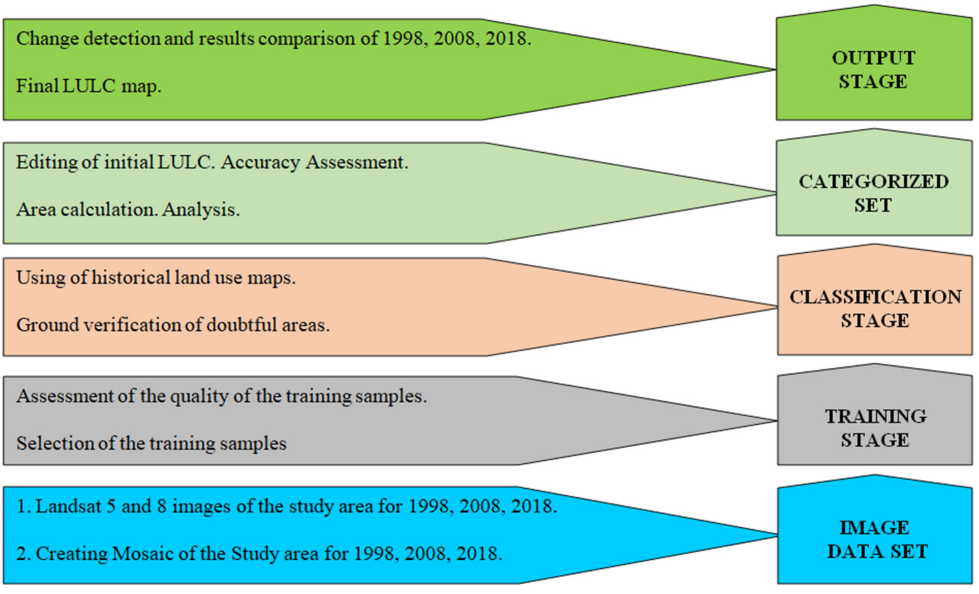

Fig. 2. Methodology for LULC Map Generation

 https://doi.org/10.1051/e3sconf/202338605013

3 Results and discussion

3.1 Results

3.1.1 Overall LULC Changes

The results of the classification of the LULC change showed that the area of agricultural Land (arable land, pastures), as well as water bodies, forests, and built-up areas, over the years of the research underwent relative changes, as shown in the LULC maps of 1998, 2008, and 2018 (Figure 3).

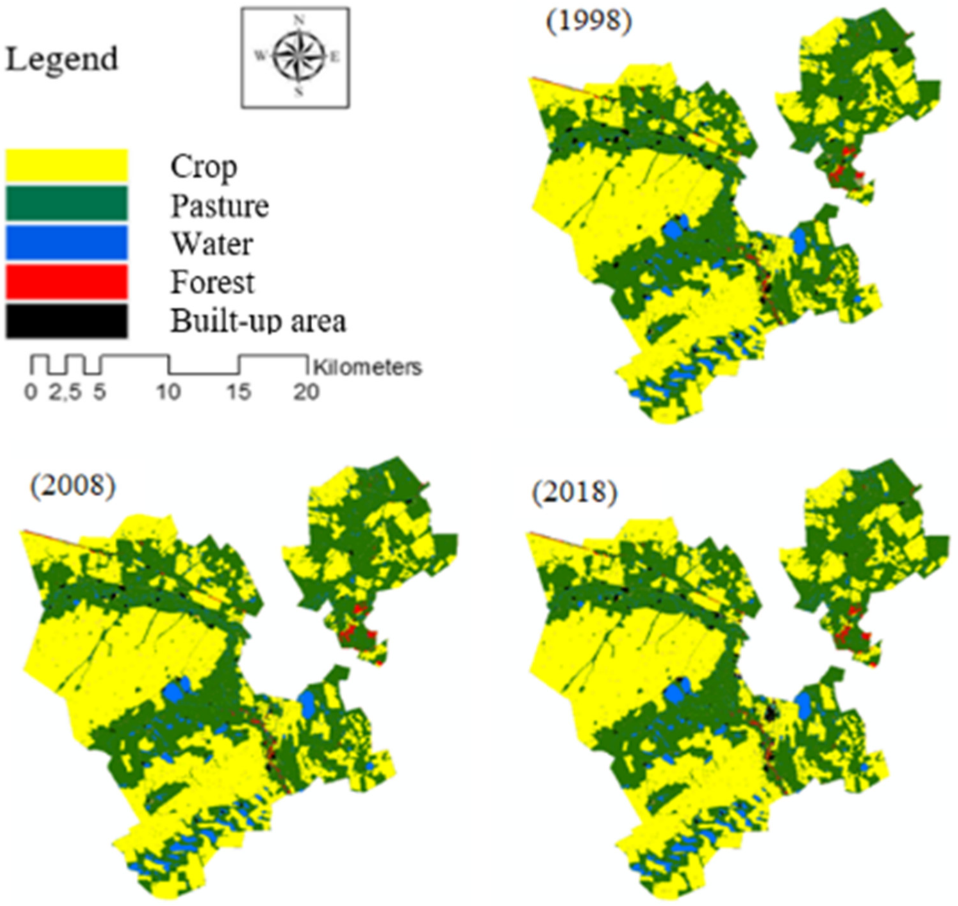

Fig. 3. LULC map of Tselinograd district after classification of Landsat mosaics in 1998, 2008, and 2018 into five classes: arable lands, pastures, water, forest, and built-up areas.

Agricultural lands (arable lands, pastures) occupy the main part of the study area (~95%), water ~ 3.6%, forests ~ 0.6%, and built-up areas ~ 0.5-0.7%.

Examples of changes in the LULC class areas from 1998 to 2018 are shown in Figure 4. The results of the LULC classification for the 1998–2018 period are shown in Table 3, which indicates that during the years of observation, about 95% of the area was occupied by arable land and pastures. For example, in 1998 and 2008, they were 95.3%, and in 2018 - 95.0%.

We found a tendency to steadily increase the area of arable land mainly due to the plowing of pastures and an increase in the area of built-up territory. A strong increase in the share of arable land occurred from 1998 to 2008. The territories occupied by arable land over the years have increased by 0.4% or 19.9 km2. Between 2008 and 2018, the rate of development of arable land decreased and amounted to only 0.1% or 11.0 km2. For the entire observation period, from 1998 to 2018, the total area of arable land increased by 0.4% or 30.9 km2. At the same time, the rangelands of the region from 1998 to 2008 decreased by 0.3% or 23.1 km2, and from 2008 to 2018 - by 0.4% or 29.6 km2. Over the entire observation period, the area of pastures decreased by 0.7% or 52.7 km2, of which 30.9 km2 was developed for arable land. A typical example of expanding the area under crops due to the plowing of pastures is shown in figure 4A. We found a tendency to steadily increase the area of arable land mainly due to the plowing of pastures and an increase in the area of built-up territory. A strong increase in the share of arable land occurred from 1998 to 2008. The territories occupied by arable land over the years have increased by 0.4% or 19.9 km2. Between 2008 and 2018, the rate of development of arable land decreased and amounted to only 0.1% or 11.0 km2. For the entire observation period, i.e. From 1998 to 2018, the total area of arable land increased by 0.4% or 30.9 km2. At the same time, the rangelands of the region from 1998 to 2008 decreased by 0.3% or 23.1 km2, and from 2008 to 2018 - by 0.4% or 29.6 km2. Over the entire observation period, the area of pastures decreased by 0.7% or 52.7 km2, of which 30.9 km2 was developed for arable land. A typical example of expanding the area under crops due to the plowing of pastures is shown in figure 4A. The area of water bodies that united many small and medium shallow lakes and rivers amounted to 3.6%. Decreases in the water mirror in these reservoirs were noted at the end of summer and the beginning of autumn, which is seen in Figure 4B. But, then they again restored to their previous level, therefore, over the years of research, the total area of water bodies remained constant.

Forest areas in the district occupied less than one percent (0.6%). At the same time, we found that the area used for growing trees has increased markedly, mainly due to the expansion of the land of previously existing forestry, which was previously used as pasture. For example, in 2008, the area of land occupied by forests, compared with 1998, increased by 0.1% or 2.1 km2. From 2008 to 2018, forest areas continued to increase. An example of increasing the area of forest stands can be seen in figure 4C. By 2018, the total area of forest stands increased by 5.8% or 2.8 km2 compared to 1998.

Urban areas occupied only 0.5%–0.6% of the entire AOI. However, the proximity of the capital of the republic had a significant impact on the change in urban areas. The most profound changes occurred near the border of the capital, the city of Nur-Sultan (figure 4D). From 1998 to 2008, the area of urbanized areas of the district increased slightly - they became the largest by 3% or 1.1 km2. Dramatic

changes occurred from 2008 to 2018, when the area of built-up territories increased by 49.6% compared

to 1998, or by 17.9 km2. For the entire period from 1998 to 2018, the total area of settlements increased by 52.6% or 19.0 km2 compared to the beginning of our observations. These changes occurred mainly due to the seizure of agricultural land, more precisely - grazing land.

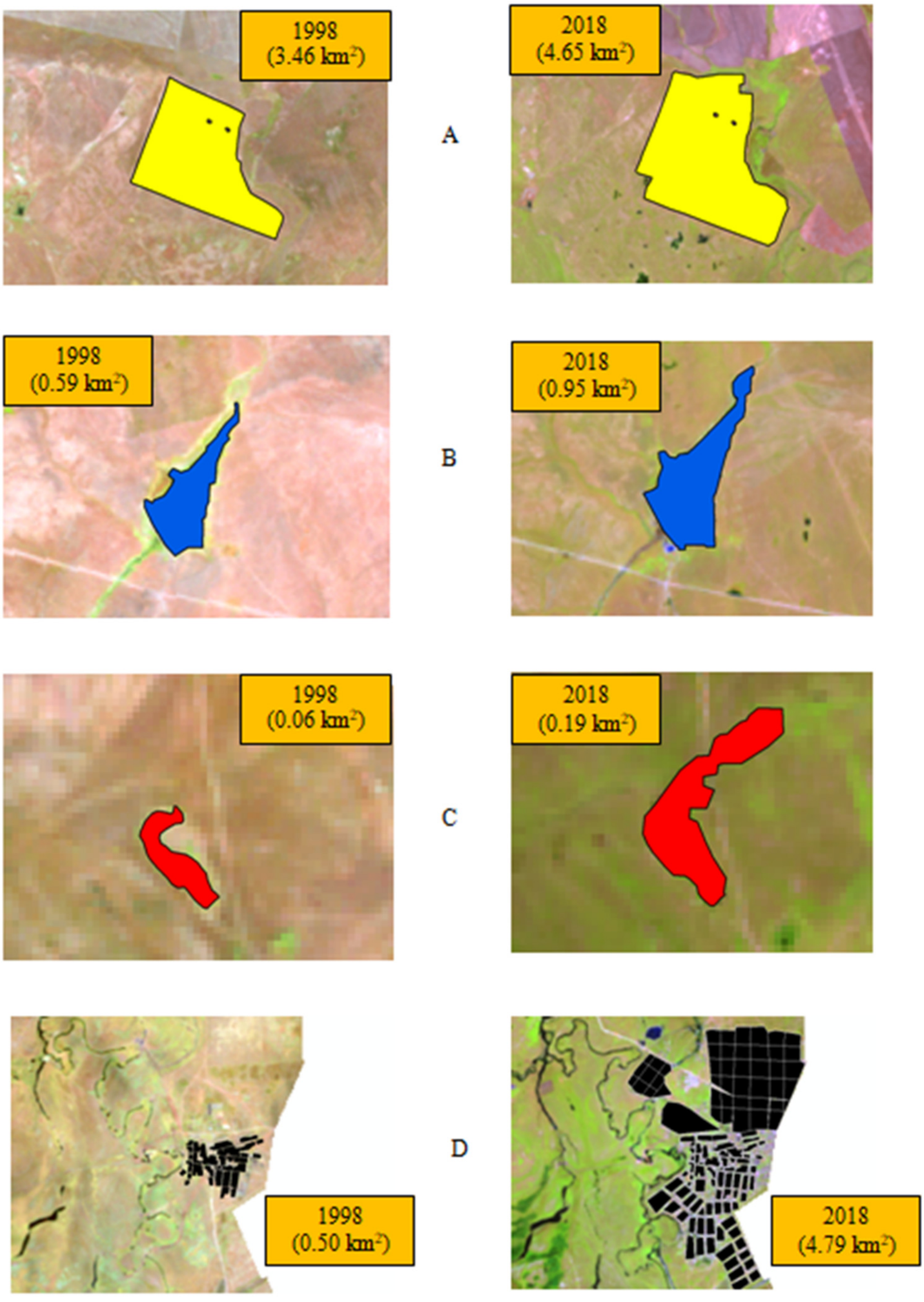

Fig. 4.. Examples of changes in the LULL classes areas from 1998 to 2018:
A – Arable lands, B – Water body, C – Forest, D – Built-up area

3.1.2 Classification Accuracy.

The overall accuracy and Kappa coefficient show that the classification results are quite reliable (Table 3). Thus, the overall classification accuracy varied between 92.7% and 94.4%. The kappa coefficient for the classified images of 1998 was 0.88, for 2008 it was 0.87, and for 2018 it was 0.90.

Table 3. LULC area, area difference, classification accuracy, and Kappa statistics

LULC Classes	**Area**						**Area difference (km^2)**		
	1998		**2008**		**2018**		**1998-2008**	**2008-2018**	**1998-2018**
	km^2	**%**	**km^2**	**%**	**km^2**	**%**			
Arable land	3922.2	50.2	3942.1	50.5	3953.1	50.6	19.9	11.0	30.9
Pasture	3523.6	45,1	3500.5	44.8	3470,9	44.4	-23,1	-29.6	-52.7
Water	283.4	3.6	283.4	3.6	283.4	3.6	0.0	0.0	0.0
Forest	47.9	0.6	50.0	0.6	50.7	0.6	2.1	0.7	2.8
Built-up area	36.1	0.5	37.2	0.5	55.1	0.7	1.1	17.9	19.0
Total	7813.2	100.0	7813.2	100.0	7813.2	100.0			
Overall accuracy (%)	93.5		92.7		94.4				
Kappa	0.88		0.87		0.90				

For each classified group, the difference in the accuracy between the producers and the users was relatively small (Table 4).

Table 4. Producer's and User's Accuracy and Commission and Omission errors of LULC classification of the study area

*LULC classes	**Producer's and User's Accuracy, %						***Errors					
	1998		2008		2018		1998		2008		2018	
	**P	U	P	U	P	U	***C	O	C	O	C	O
1	93.8	93.6	92.1	93.5	93.9	95.3	6.3	6.4	7.9	6.5	6.2	7.7
2	92.8	92.9	92.8	91.2	94.6	93.0	7.2	7.1	7.3	8.8	5.4	7.0
3	98.6	99.2	99.5	99.5	99.5	99.5	1.4	0.8	0.6	0.6	0.6	0.6
4	95.1	98.3	95.3	93.9	95.4	95.4	3.3	1.7	4.7	6.2	4.6	4.6
5	95.7	95.7	93.8	91.8	95.8	95.8	4.4	4.4	6.3	8.2	4.2	4.2

*1 – Arable land, 2 – Pasture, 3 – Water, 4 – Forest, 5- Built-up area
**P - Producer's, U - User's,
***C – Commission, O - Omission

For example, for arable land, producer accuracy varied from 92.1% to 93.9%; for pastures from 92.8% to 94.6%; for water from 98.6% to 99.5%; for forest from 95.1% to 95.4%; and for the built-up area from 93.8% to 95.7%. User's accuracy was found in even smaller intervals, and for all classified groups varied from 91.2% to 99.5%. Since the overall accuracy exceeded 90%, the research results could be considered quite acceptable for both the user and the producer.

Another confirmation of the reliability of image classification is the low values of the errors of omission (Commission) and omission (Omission) (Table 4). So, for the 1998 image, omission errors in different LULC classes ranged from 1.4 to 7.2; for the image of 2008 - from 0.6 to 7.9; and for 2018 - from 0.6 to 6.2. The values of skipping errors fluctuated around the same limits: in 1998, from 0.8 to 7.1; in 2008 from 0.6 to 8.8 and in 2018 from 0.6 to 7.7.

That is, the results of evaluating the classification accuracy and their errors convincingly showed the reliability of the work we performed and paved the way for automating thematic mapping processes for LULC classification results.

3.2 Discussion

Urbanization is primarily associated with an increase in the number of urban residents [40], and is usually accompanied by the expansion of the city into agricultural land [41,42]. Kazakhstan is no exception [43]. During the 1996–2015 period, the urban population increased by 16.6%. One of the points of migration attraction was the city of Nur Sultan. As the capital, it forms the supporting spatial framework of the country [44] and is the center of the settlement, which is accompanied by urban expansion. For example, instrumental, to the use of GIT, a strong land expansion by the city of Nur Sultan from 1990 to 2016 was shown [45]. So, the area of land occupied by this metropolis only from 1998 to 2018 increased almost threefold - from 258 km2 to 797.3 km2 [13], and this happened as a result of the seizure of lands that were previously used for the most part for agricultural purposes. Along with the land expansion, there was an increase in the population of the capital, which also grew more than three times [46].

Economic growth is one of the main drivers [40] that push urban expansion into the PUA. For example, affordable land in the PUA attracts new immigrants. The expansion process in the PUA is very beneficial when the price of the converted land (from agriculture to buildings) is several times higher than the price of the same agricultural land. Besides, almost all agricultural land in the PUA is available for market transactions, so agricultural land is relatively easy to buy and sell [47]. For these reasons, land speculation is very common in these areas. The same is true for the study area [48].

On the other hand, since urban expansion into agricultural land is officially limited [49], the government of the republic cannot speed up planning procedures to manage urban expansion in the PUA [50]. In addition, at the level of the country's government, a system of measures was adopted aimed at the sustainable development of the Astana (Nur-Sultan) agglomerations along with their PUAs, including the Tselinograd district [51]. These measures are aimed at restraining the growth of the city and improving the environment, including the creation of a green framework around urban agglomerations in the form of forest stands [52], which explains the increase in the forested area in the AOI.

4 Conclusions

We studied the spatiotemporal changes of LULC of the Tselinograd district, which is within the PUA of the fast-growing metropolis Nur-Sultan. Using multi-temporal Landsat images for 1998, 2008, and 2018, five categories of land were classified (arable land, pastures, water bodies, forest, and built-up areas). As a result, the main trends of the influence of the fast-growing large city on the change in the structure of the LULC in the agricultural district were identified.

From 1998 to 2018 the following observations were made: there was a significant increase in arable land and a decrease in pasture land; the area of water bodies varied within the seasons, but no general trend of their increase or decrease was found; a steady increase in the area occupied by forest stands was noted; the most active increase in built-up areas is observed at the border of the AOI with the capital of the republic. The results obtained were reliable and characterized by fairly high accuracy.

The analysis of factors influencing the sustainable development of the PUA showed that the most powerful drivers of the impact of the Nur-Sultan metropolis on the Tselinograd district are the expansion of agricultural land, city population growth, and the systems of economic and legislative measures aimed at preventing the spontaneous development of urban sprawl. On the other hand, the increase in the area of cultivated land in the AOI is due to their abandonment after the collapse of the former USSR, which was caused by the economic recession. In general, the system of measures adopted at the state level was aimed at the sustainable development of the Tselinograd district.

The results of our research, based on the use GIT, are of considerable value. They contribute to the detection of changes in the composition of LULC in a semi-automatic mode and are extremely useful for the rapid identification and assessment of phenomena and processes in PUAs that do not correspond to the sustainable development of the study area.

Funding

This research has been funded by the Ministry of Agriculture of the Republic of Kazakhstan (BR 10764919).

References

1. K. Nilsson, S. Pauleit and et al, *Peri-urban Futures Scenarios and Models for Land Use Change in Europe*, 36 (Publisher Springer Heidelberg New York Dordrecht, London, 2013)
2. F. M. Adedire, *Peri-urban Expansion in Ikorodu Lagos Extent Causes Effects and Policy Response,* Urban Forum, **29,** 259-275 (2018)
3. J. L. Barros, A. O. Tavares, M. Monteiro, P. P. Santos, *Peri-Urbanization and Rurbanization in Leiria City,* the Importance of a Planning Framework Sustainability, **10,** 2501(2018)
4. A. Wandl, M. Magoni, *Sustainable Planning of PeriUrban Areas*, Introduction to the Special Issue Planning Practice & Research, **32** (1), 1-3(2017)
5. O. Appiahd, D. Schröder, E. K. Forkuo, J. T. Bugri, *Application of Geo-Information Techniques in Land Use and Land Cover Change Analysis in a Peri-Urban District of Ghana,* Int. J. of Geo-Information, **4,** 1265-1289(2015)
6. T. E. Parece, J. B. Campbell, *Land Use/Land Cover Monitoring and Geospatial Technologies*, An Overview In book, Advances in Watershed Science and Assessment, The Handbook of Environmental Chemistry, Chapter 1 Eds, T. Younos, T. E. Parece, 33 (Publisher: Springer, 2015)
7. C. Liping, S. Yujun, S. Saeed, *Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques* -A case study of a hilly area, Jiangle, PLoS ONE, **13** (China, 2018)
8. *GISGEOGRAPHY,* **10,** Best Free Land Cover/Land Use Data (2022)
9. Y. Wu, H. Wang, Z. Wang, B. Zhang, C. Burghard, B. C. Meye, *Knowledge Mapping Analysis of Rural Landscape Using Cite Space,* Sustainability, **12**, (66) (2020)
10. M. Juliev, A. Pulatov, S. Fuchs, J. Hübl, *Analysis of Land Use Land Cover Change Detection of Bostanlik District*, *Uzbekistan*, Pol. J. Environ. Stud**., 28** (5), 3235-3242 (2019)
11. P. Christiansen, T. Loftsgarden, *Drivers behind urban sprawl in Europe,* 1TØI Report 1136/2011, 41 (2011)
12. J. Wang, S. Qu, K. Peng, Y. Feng, *Quantifying Urban Sprawl and Its Driving Forces*

in China, Discrete Dynamics in Nature and Society*,* **5**, 1-14 (2019)

13. Nur-Sultan City Akimat, http://astana.gov.kz/en/
14. Sultangazin. Umirzak. Makhmutovich, *Selected Works 1996-2006,* 420 (Space Research Institute, Almaty, in Russia, 2006)
15. E. A. Zakarin, B. M. Mirkarimova, T. V. Dedova, *Geoinformation models of atmospheric pollution of the Aral-Caspian region of Kazakhstan,*. 108 ("CaTa", Almaty, 2007)
16. T. Musabaev, *Space research and experiments of the Republic of Kazakhstan (2005-2007),* Kazakhstan space research, National Space Agency **2**, 240 (LLP "Dyke-Press, Almaty, 2008)
17. T. Musabaev, Zh, Zhantayev, *Applied space research in Kazakhstan,* Kazakhstan space research, **6**, 368 (LLP "Dyke-Press", Almaty, 2010)
18. D. Sh. Akhmedov, Zh. Sh. Zhantaev, M. M. Moldabekov, N. R. Muratova, T. A. Musabaev, L. F. Spivak, U. M. Sultangazin, *Fundamental and applied research on the development and implementation of modern space technologies in the interests of socio-economic development of the Republic of Kazakhstan for 1994-2009,* 160 (Triumph "T", Almaty, 2011)
19. O. Alipbeki, G. Kabzhanova, G. Kurmanova, Ch Alipbekova, *Application of GIS technology to monitor the secondary radioactive contamination of the Degelen mountain massif*, 8th IGRSM Int. Conf. and Exhibition on Geospatial and Remote Sensing Kuala Lumpur Malaysia (2016)
20. O. Alipbeki, G. Kabzhanova, Ch Alipbekova, *Carrying out space monitoring of agricultural production in North Kazakhstan,* Eurasian Union of Scientists, **23** (2), 153-156 (2016)
21. G. Kabzhanova, K. Baktybekov, A. Aimbetov, A. Kurmasheva, G. Kabdulova, *Remote monitoring of the main types of soil in Northern Kazakhstan,* Seventh Int. Conf. on Remote Sensing and Geoinformation of the Environment, **27** (2019)
22. G. Kabdulova, G. Kabzhanova, K. Baktybekov, A. Aimbetov, L. Aligazhiyeva, *Satellite remote sensing for monitoring of the forest resources of Kazakhstan,* Seventh Int. Conf. on Remote Sensing and Geoinformation of the Environment*,* **27 (**2019**)**
23. A. Hamidov, K. Helming, D. Balla, *Impact of agricultural land use in Central Asia*: a review Agronomy for Sustainable Development, **36** (6) (2016)
24. K. Samarkhanov, J. Abuduwaili, A. Samat, G. Issanova, *The Spatial and Temporal Land Cover Patterns of the Qazaly Irrigation Zone in 2003–2018: The Case of Syrdarya River's Lower Reaches*, Sustainability, **11,** 4035 (Kazakhstan, 2019)
25. R. Kraemer, A. V. Prishchepov, D. Müller, T. Kuemmerle, V. C. Radelof, A. Dara, A. Terekhov, M. Frühauf, *Long-term agricultural land-cover change and potential for cropland expansion in the former Virgin Lands area of Kazakhstan,* Environmental Research Letters, **10** (5), 054012 (2015)
26. Ch. Eisfelder, M. Markus. Niklaus, C. Kuenzer, *Net primary productivity in Kazakhstan, its spatio-temporal patterns and relation to meteorological variables,* Journal of Arid Environments, **103,** 17-30 (2014)
27. Zh. Taibassarova, Nazarbayev, *Detection of the vegetation change cover using Landsat TM5 in the Burabay State National Natural Park Kazakhstan,* Nazarbayev University (Astana)

28. SRTM DATA Available online: http://srtm.csi.cgiar.org/
29. Official internet resource of Tselinograd district: http://selinograd.akmo.gov.kz/content/4791-29-05-18-09-50-07-karta-celinogradskogo-rayona
30. *Aagroclimatic resources of the Akmola region*: a scientific-applied reference book Ed. C. C. Baysholanova, 133 (Astana, 2017)
31. *United States Geological Survey* https://earthexplorer.usgs.gov/
32. https://developers.google.com/earth-engine/datasets/catalog/landsat
33. https://developers.google.com/earth-engine/datasets/catalog/sentinel
34. *Automated information system of the state land cadastre of the Republic of Kazakhstan and technical support*
35. M. Bossard, J. Feranec, J Otahel, *CORINE Land Cover Technical Guide – Addendum* 2000 Technical report No. 40/2000. (Copenhagen, 2000)
36. H. A. Kaul, I. T. Sopan, *Land Use Land Cover Classification and Change Detection Using High-Resolution Temporal Satellite Data,* Journal of Environment. **1** (4), 146-152 (2012)
37. T. B. P. Nguyen, X. Zhang, W. Wu, H. Liu, *Land Use/Land Cover Changes from 1995 to 2017 in Trang Bang*, Southern Vietnam, J. Agricultural Sciences, **10,** 413-422 (2019)
38. https://desktop.arcgis.com/en/arcmap/10.6/tools/spatial-analyst-toolbox/maximum-likelihood-classification.htm
39. I. K. Lurie, A. G. Kosikov, *Theory and practice of digital image processing,* 168 (Scientific World, Moscow, 2003)
40. *World Urbanization Prospects:* The 2018 Revision United Nations, Department of Economic and Social Affairs Population Division New York, **126 (**2019**)**
41. G. Worku, *Assessing the effects of urban expansion on farm land The case of Tefki town*, Academic Paper, **16** (2019)
42. M. Lasisi, A. Popoola, A. Adediji, A. Oluwatola, K. Babalola, *City Expansion and Agricultural Land Loss within the Peri-Urban Area of Osun State, Nigeria, Ghana,* Journal of Geography, **9** (3), 132-163 (2017)
43. *National report of the Republic of Kazakhstan on housing and sustainable urban development*. Habitat III, **45** (Astana, 2016)
44. *The dynamics of the development of Astana for 18 years*
45. A. Ilyassova, N. L. Kantakumar, D Boyd, *Urban growth analysis and simulations using cellular automata and geo-informatics: comparison between Almaty and Astana in Kazakhstan*, Geocarto International Correction, **36** (5) (2021)
46. *The population of Nur-Sultan* Wikipedia.
47. World Bank Group, *A new growth model for building a secure middle-class* Kazakhstan Systematic Country Diagnostic Report No. 125611-KZ, 154 (2018)
48. A. S. Kulmaganbetova, K. K. Abuov, N. Z. Akhmetova, *Development of the Land Market in the Republic of Kazakhstan,* European Research Studies Journal, **21** (4), 545-556 (2018)
49. *The land code of the Republic of Kazakhstan* (as amended and supplemented as of 10.01 (2022)

50. *Kazakhstan land administration report* USAID, 47 (2005)
51. *On approval of the interregional territorial development scheme of the Astana agglomeration* (2017)
52. *The sixth national report on biological diversity in the Republic of Kazakhstan*, 227 (Astana, 2018)