Spatiotemporal analysis and identifying the driving forces of land use change in the Abay district (Karagandy Region, Kazakhstan)

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Abstract. Land use and cover change (LUCC) affects the nature of human activities in a particular area. Therefore, the manifestation of the driving forces of these changes plays a decisive role. This paper analyses the LULC dynamics of the Abay district of Karagandy oblast from 2016 to 2023. The study's main objective is to find the driving forces of land use based on the integrated assessment of spatio-temporal data (STD) and socio-economic, climatic and environmental indicators (SECEI). Classification of Sentinel-2 images into LULC classes is carried out using the Random Forest (RF) algorithm on the Google Earth Engine (GEE) platform. The driving factors were assessed using principal component analysis (PCA) and linear regression (LR). The results obtained can be used to guide the development planning of the territory.

1 Introduction

Studying Land use and Land-Cover changes through Spatiotemporal data is essential to understanding and managing natural resources and achieving SDGs [1]. Well-chosen LULC classes can provide comprehensive information on changes in urban areas, agricultural lands, forests, water bodies and other components of the environment [2]. Analysis of LULC changes provides essential information for identifying driving factors [3] and making decisions in planning, environmental protection and territorial management [4].

In recent years, RS methods have become essential for studying LULC due to the contactless acquisition of information about the Earth's surface. They allow for obtaining interval data series with high accuracy, which is especially important for creating multi-row

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maps with different intervals [5]. At the same time, using the Machine Learning (ML) method as an RF algorithm allows for reliable classification and analysis of LULC [6]. ML algorithms use large amounts of data to identify key features of different LULC classes, which leads to confident identification of changes in the studied areas [7].

A critical step in studying LULC changes is identifying the driving factors of land use, which is necessary for effective long-term planning and management decisions for sustainable development. Forecasting changes by integrating LULC with SCEI is of considerable value [8,9].

Studies based on the LULC long-term series classification in Kazakhstan were carried out for the Arshaly [10], Shortandy [11], Tselinograd [12], Burabay [13], Korgalzhyn districts [14] of the Akmola oblast and the Talas district [15] of the Zhambyl oblast. They were aimed at assessing the impact of the change in LULC of a large city [10-12], the complex effects of STD and SCEI on sustainable development [13], and also to predict the development of individual classes using CA-ANN [14] and RF [15]. However, studies to determine the driving forces of LULC changes, considering SCEI based on PCA and linear regression equations, were conducted only for the Burabay district of the Akmola oblast. Unfortunately, no studies are in this direction for the Abay district of the Karagandy oblast.

2 Objective

The main objective of this study is to identify the driving forces that contribute to LULC changes in the Abay district of Karagandy region based on RS data and statistical indicators. To achieve this goal, several critical tasks need to be solved:

- analyse current LULC changes in the area based on time series of satellite data;
- determine the main socio-economic, climatic and spatial-temporal data factors influencing LULC changes using PCA and linear regression methods;
- identify the main driving factors influencing LULC dynamics.

3 Materials and methods

This study uses an integrated approach to analyze LULC changes in the Abay district of Karagandy oblast. The main tools are Sentinel-2 satellite data processed using the EE platform [16]. The RF machine learning algorithm was used to classify LULC. PCA analysis and construction of linear regression models were performed in the IBM SPSS Statistics software package [17]. These methods allow us to accurately assess LULC changes, considering both spatial and temporal factors. The research methodology is presented in Figure 1.

3.1 Study area

Abay district is located in the central part of Kazakhstan, in the Karagandy oblast of Kazakhstan (Figure 2), at 49°30′ north latitude and 73°30′ east longitude. It borders on the Aktogay and Bukhar-Zhyrau districts of the Karagandy oblast and the Zhanarka district of the Ulytau oblast.

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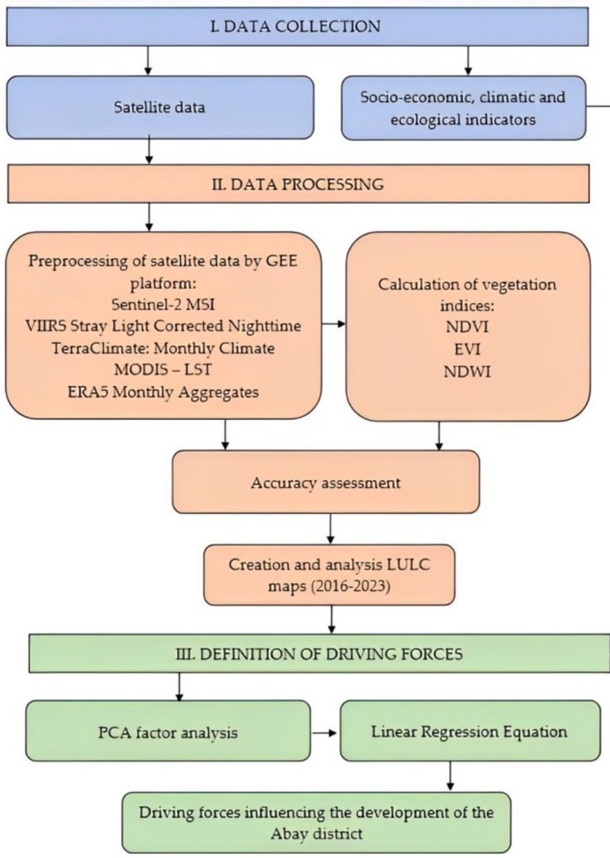

Fig. 1. Research methodology.

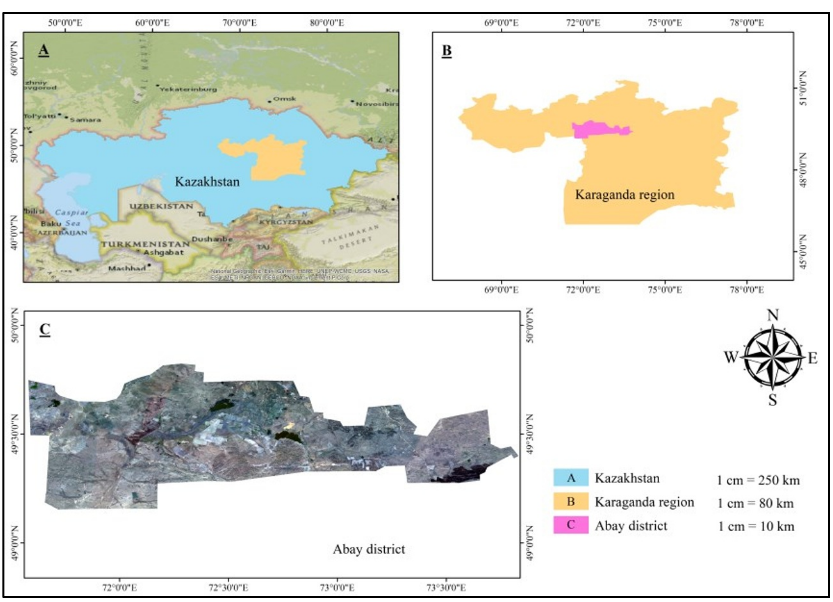

Fig. 2. Location of the Abay district.

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The region's climate is continental, characterised by cold winters and hot summers. Average winter temperatures range from -15 °C to -20 °C, and summer temperatures from +20 °C to +30 °C. Precipitation occurs mainly in the summer, with an average annual amount of about 200-300 mm. The Abay district is primarily represented by steppe and semi-desert landscapes. Small reservoirs located in the area play an essential role in maintaining biodiversity. In addition, a significant part of the territory is used as pastures. The area is an important industrial centre home to coal mines, construction industry enterprises, machine-building, and metallurgical plants. These enterprises play a vital role in the region's economy, producing coal, building materials, metal structures and equipment for various industries [18].

3.2 Data Collection and Processing

3.2.1 Satellite and Statistical Data Collection

Data were collected to conduct the analysis studies, which were divided into two categories. The first includes SCEI obtained from the National Bureau of Statistics of the Republic of Kazakhstan [19]. This category contains population size, average monthly nominal wage, fixed capital investment, gross agricultural output, social security level, and environmental indicators. The second category includes STDs containing information from Sentinel-2 and other satellite images (Table 1) that were collected and processed in the GEE platform. Satellite data were used to obtain climate indicators such as precipitation, average annual temperature, and temperature during the vegetation period. Additionally, vegetation indices such as NDVI, NDWI, and EVI were included [20-22].

Table 1. Satellite dataset characteristics.

Data Sets	Bands	Resolution
Sentinel-2 MSI: MultiSpectral Instrument	B1-B12	10-60 m
VIIRS Stray Light Corrected Nighttime	avg_rad	463.83 m
TerraClimate: Monthly Climate	Pr	4638.3 m
MODIS - LST	LST_Day_1km	1000 m
ERA5 Monthly Aggregates	total_precipitation	27830 m

3.2.2 LULC Classification

The LULC classification in the Abay district into five classes was carried out using Sentinel-2 images from 2016 to 2023. For this purpose, the RF algorithm on the GEE platform was used, which made it possible to classify the territory into five main classes.
Water Resources (WR) - this class includes all large water bodies and objects in the study area. It contains rivers, local lakes and other permanent or seasonal water masses. Urban Areas (UA) - this class includes all industrial zones and territories of populated areas, including residential buildings and commercial and industrial infrastructure. Wetlands (WL) – this class includes forest vegetation, forest plantations and vegetation located in wetlands. Steppe Vegetation (SV) – steppe vegetation is the most common class in the study area. Small-growing grasses, typical for dry steppes, represent it Cropland (CR) - this class includes all types of arable and agricultural land. These lands are characterized by a high degree of human activity, which provides for ploughing, sowing, tending crops and harvesting. Cropland occupies significant areas in the study area and is a crucial source of food and economic activity.

Each Sentinel-2 image limited to the study area was selected with a cloudiness threshold of 20%, and a scene of the area during the vegetation period was created using the median method [23]. Based on this scene, the vegetation indices NDVI, EVI and NDWI were calculated and used to train the model using RF. This ensured high classification accuracy and allowed a detailed study of the changes in each class during the specified period.

3.2.3 Evaluation of the accuracy of LULC classifications

To test the accuracy of the LULC classification, a test dataset was used, which included 350 control points. These points were selected using random stratified sampling, which allowed for spatial distribution and ensured representativeness for all LULC classes, including those that occupy small areas, such as urban areas.

The classification accuracy performed using the RF algorithm was assessed using the Confusing matrix (CM), which allowed the calculation of crucial accuracy metrics such as Overall Accuracy (OA), User's Accuracy (UA) and Producer's Accuracy (PA) [24]. In addition to these metrics, Quantity Disagreement (QD) and Allocation Disagreement (AD) metrics were used. QD measures the error associated with the incorrect assignment of pixels to different classes by assessing the difference between the predicted and actual distributions of pixels across classes. AD assesses the degree of incorrect spatial placement of pixels [25].

3.3 Identifying Driving Factors of Land Use and Land Cover Classes

3.3.1 Principal Component Analysis

Principal Component Analysis, a widely used statistical technique, is versatile in its ability to reduce the dimensionality of data while preserving maximum variability of information. By identifying principal components, which are linear combinations of the original variables, PCA effectively reduces the number of original variables. These components explain most of the variability in the original data and can be harnessed for a wide range of further analysis and the construction of predictive models [26]. This versatility inspires researchers to explore its potential in various applications.

This study used PCA to identify critical factors influencing changes in LULC classes. The variables included in the analysis were population, average monthly nominal wage, fixed capital investment, gross agricultural output, social security, precipitation, average annual temperature, temperature during the growing season, and vegetation indices NDVI, NDWI, and EVI. PCA allowed us to identify the most significant components, which were then used to build linear regression models.

3.3.2 Linear Regression Equations

A regression model was constructed based on the identified principal components. These models consider the influence of various factors on each class, which allows for an accurate assessment of their impact on LULC changes. The generalised formula for all classes is as follows:

$$LULC=\beta_i+\gamma_{1-i}C_1+\gamma_{2-i}C_2+\cdots+\gamma_{n-i}C_{n\text{-}f} \qquad (1)$$

where βi is a constant term related to a specific class, $\gamma 1-i$, $\gamma 2-i$, $\gamma n-i$ are coefficients that determine the contribution of each of the principal components $C1$ and $C2$ to the change in the corresponding class *i*. These equations allow us to model the changes in each LULC class based on the components extracted from PCA.

4 Results and discussion

4.1 LULC Classification Accuracy Assessment

The accuracy assessment based on the Confusion Matrix for LULC classifications from 2016 to 2023 yielded the results in Table 2. The average OA value was 0.90 ± 0.01. UA reached 0.90 ± 0.01, and PA - 0.91 ± 0.02. These indicators confirm the high accuracy of the classification.

Table 2. Accuracy assessment results.

Year	OA	PA	UA	AD	QD
2016	0.87	0.88	0.87	8.4	1.6
2017	0.91	0.91	0.91	6.8	2.4
2018	0.89	0.89	0.89	7.4	1.8
2019	0.91	0.92	0.91	6.2	2.4
2020	0.91	0.91	0.91	7.4	1.8
2021	0.91	0.93	0.91	6.2	2.4
2022	0.89	0.88	0.89	8.4	1.6
2023	0.92	0.92	0.92	6.6	1.6
Average	0.90±0.01	0.91±0.02	0.90±0.01	7.18±0.73	1.95±0.34

4.2 Analysis of LULC changes

Significant changes in LULC classes occurred between 2016 and 2023 in the study area, as reflected in Table 3 and (Figure 3).

Table 3. Distribution of LULC in the Abay District in ha.

Year	WR	UA	WL	SV	CR	Total
2016	9670.82	6418.11	30266.28	550703.21	52941.57	65000
2017	9872.45	6560.83	33785.31	543817.32	55964.08	65000
2018	10048.71	6873.61	36722.49	536534.43	59820.76	65000
2019	10258.44	6985.61	32094.66	536478.60	64182.69	65000
2020	10250.34	7082.86	33786.65	533413.39	65466.76	65000
2021	10176.13	7112.64	33203.90	529691.46	69815.86	65000
2022	10274.95	7354.28	32471.33	530055.61	69843.83	65000
2023	10197.82	7580.81	35188.11	526528.87	70504.39	65000

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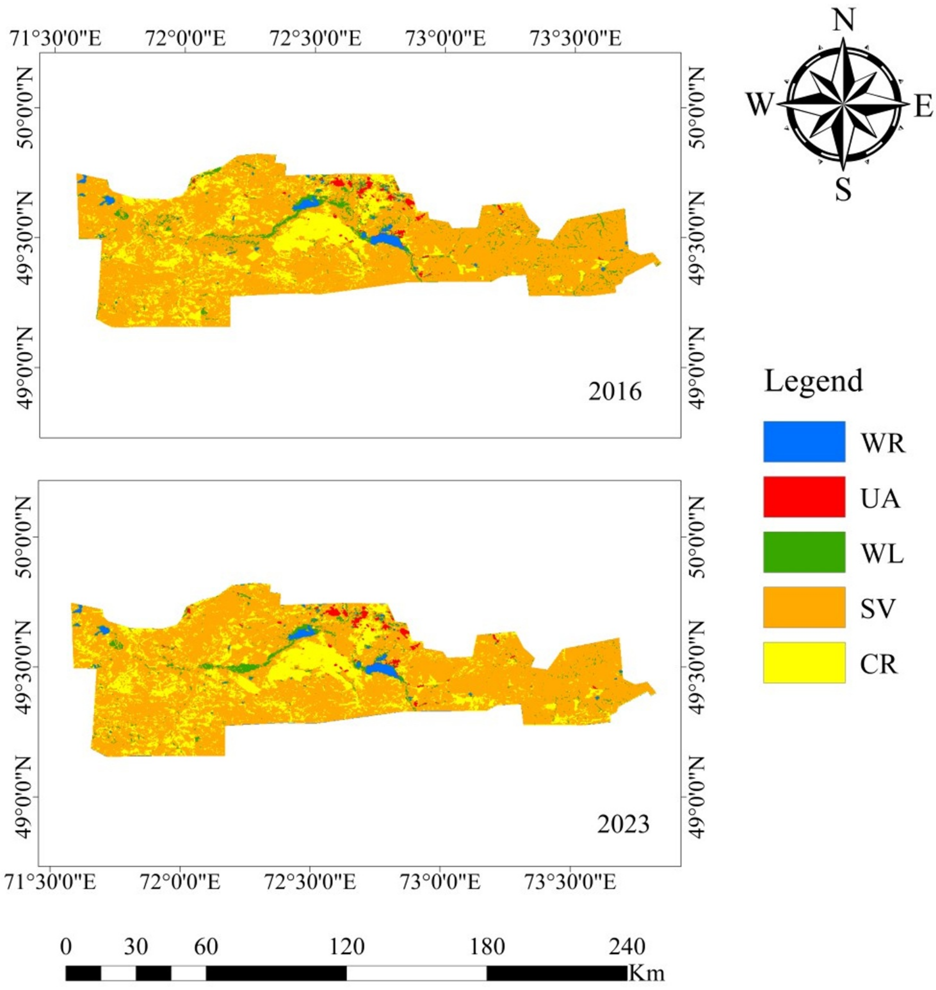

Fig. 3. LULC maps for 2016 and 2023.

By 2023, the CR class increased its area, occupying 10.85% of the district's total area. During the entire observation period from 2016 to 2023, this class increased by 2.70% of the total area. Cultivated land showed the most significant increase in area among all LULC classes in AOI.

SV occupied the most significant area share in 2016 (84.72%); by 2023, it had decreased to 81.00%, losing 3.72% of the total area. This indicates a significant decrease in steppe vegetation due to the expansion of arable land.

WL also showed positive dynamics, increasing its area from 4.66% in 2016 to 5.41% in 2023. The overall increase in class area was 0.75%.

Urbanized areas (UA), despite their relatively small area, show stable growth throughout the period, increasing from 0.99% in 2016 to 1.17% in 2023. The increase was 0.18%, indicating a moderate pace of urbanization in the AOI.

WR remained the most stable class in the area, increasing slightly from 1.49% in 2016 to 1.57% in 2023. Despite a relatively small change of 0.08% of the total area, this class showed positive dynamics, probably related to seasonal changes in precipitation.

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4.3 Identifying the drivers of LULC class changes

4.3.1 Determining the Principal Component

Factor analysis was performed to reduce the number of variables and identify the key components that explain the largest proportion of the variability in the data. Two principal components were identified: F1 and F2 (**Table 4**)

Table 4. Factor Loadings for Principal Components F1 and F2.

Variables	Component F1	Component F2
Population	0.925	0.070
Average nominal monthly wage per employee	0.949	-0.160
Investments in fixed capital	0.981	-0.009
Gross output of agricultural products (services), million tenge	0.937	-0.048
NDVI	0.066	0.936
NDWI	-0.524	0.678
EVI	0.174	0.910
Precipitation (average annual)	-0.320	0.835
LST (temperature during the vegetation period)	-0.514	0.351

The principal component (F1) explains 47.47% of the total variance. It is primarily associated with economic indicators such as population, average monthly nominal wages, fixed capital investment, and gross agricultural output. The second component (F2) explains 33.54% of the total variance. It relates to climate indicators such as average annual precipitation, temperature during the growing season, and vegetation indices (NDVI, NDWI and EVI). These results indicate that the driving forces of the development of the Abay district are economic factors.

4.3.2 Linear Regression Models

The results of the LR models for each class, taking into account all indicators, were presented as follows.

LR showed a moderate explanation of the data variability for the WR class with a relatively significant value of $R^2 = 0.773$ (adjusted $R^2 = 0.682$, $F = 8.507$, $p = 0.025$). The F1 component has a positive coefficient, indicating increased WR with increasing economic development. The F2 component has a negative coefficient, indicating a decrease in water resources with changing climate conditions.

$$WR = 1.553 + 0.029 \times F1 - 0.005 \times F2 \tag{2}$$

The LR model showed a high degree of data explanation for the UA class with a high significance of $R^2 = 0.984$ (adjusted $R^2 = 0.977$, $F = 149.594$, $p < 0.001$). Component F1 has a significant positive effect on the growth of urbanized areas, while component F2 has virtually no impact on changes in this class.

$$UA = 1.076 + 0.059 \times F1 - 0.00009958 \times F2 \tag{3}$$

The LR model for the WL class has moderate explanatory power with an acceptable significance of $R^2 = 0.765$ (adjusted $R^2 = 0.671$, $F = 8.149$, $p = 0.027$). The F1 component positively affects WL growth, while F2 also shows a positive but less pronounced effect.

$$WL = 5.145 + 0.105 \times F1 + 0.242 \times F2 \tag{4}$$

For the SV class, the LR model showed a high degree of data explanation with a significant model, where $R^2 = 0.963$ (adjusted $R^2 = 0.948$, $F = 65.198$, $p < 0.001$). The F1 component has a negative coefficient, indicating a reduction in steppe vegetation with an increase in economic indicators, and F2 also has a negative effect, but to a lesser extent.

$$SV=82.447-1.202\times F1-0.138\times F2 \quad (5)$$

LR for the CR class demonstrated a very high degree of data explanation with a significant model $R^2 = 0.964$ (adjusted $R^2 = 0.950$, $F = 67.342$, $p < 0.001$). Component F1 had a positive effect on agricultural land expansion, while component F2 had a slightly negative effect on this class.

$$CR=9.780+1.009\times F1-0.099\times F2 \quad (6)$$

5 Conclusions

In the course of the study, a comprehensive assessment of LULC changes in the territory of the Abay district of the Karagandy oblast for the period from 2016 to 2023 was carried out, and the driving forces of AOI development were identified.

The study area has seen significant changes in the distribution of different LULC classes. The most noticeable changes were recorded in steppe vegetation and agricultural land categories. Steppe vegetation has significantly decreased, giving way to agricultural land, indicating active development of farming activity in the region. The share of steppe vegetation has reduced by 3% of the area's total area, while the area of agricultural land has increased by 2.7%.

Principal component analysis showed that economic factors are the main driving force behind the Abay region's development.

Linear regression models developed for each LULC class showed high explanatory power. The models for urbanized areas ($R^2 = 0.984$) and agricultural lands ($R^2 = 0.964$) had the most significant explanatory value. These models confirm that economic and climatic factors significantly impact the dynamics of change in these classes.

Overall, this study demonstrated the importance of an integrated approach to analysing LULC changes, including spatiotemporal analysis of remote sensing data and considering socioeconomic and climatic factors. The work results may be helpful for government agencies responsible for land use management and scientists and researchers studying LULC dynamics and their impact on ecosystems.

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