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Research article

The Detection of Past and Future Land Use and Land Cover Change in Ugam Chatkal National Park, Uzbekistan, Using CA-Markov and Random Forest Machine Learning Algorithms

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Abstract

This comprehensive study investigates land use and land cover (LULC) changes in Ugam Chatkal National Park, Uzbekistan, over a 30-year period from 1993 to 2022 with Landsat satellite images. Utilizing advanced CA-Markov and Random Forest machine learning algorithms, it meticulously analyzes historical data to understand past trends and projects future LULC changes. According to remote sensing analysis of the past, our findings show the sharp decline of glacier land cover from 2105 km^2 to 1334 km^2 in the Ugam Chatkal National Park, replaced by tree cover (from 327 km^2 in 1993 to 450 km^2 in 2022), rangelands (1259 km^2 in 1993 to 1355 km^2 in 2020), and rocks (from 834 km^2 in 1993 to 1390 km^2 in 2022). Agriculture, water, and bare land witnessed some fluctuations but did not change significantly. At the same time, the region experienced some urbanization, raising the urban area from 50 km^2 in 1993 to 90 km^2 after 29 years. The article suggests three possible scenarios for the future of the region: "hard," "soft" and "bad" scenarios. Land cover change predictions are made in TerrSet software with the CA-Markov model for four decades: 2035, 2045,2055, and 2065. Hard and soft scenarios predict similar patterns for the future: a decline in glacier cover and a rise of tree cover, rock, and rangelands, with a slight increase in agriculture and urban classes. Whereas "bad" scenario, which incorporates rapid urbanization and agricultural expansion for the study area, forecasts a climb of the urban area until 415 km^2 (8% of the territory) until 2065, and 286 km^2 for agriculture.

Keywords: LULC; CA-Markov; Uzbekistan ; Random Forest

1. Introduction

In the 21st century, many problems threaten our planet, and over the coming decades, the scale of the changes foreseeably will continue to grow. Land-use and land-cover (LULC) altercation is arguably one of the most prominent of many environmental issues the planet is currently experiencing (ESCOBAR, A., 2012; Gómez *et al.,* 2016; Mustard *et al.,* 2012). Numerous ecosystem processes and services (biodiversity, hydrology, temperature, carbon cycle, soil fertility) are impacted by the process of land use and the change in land cover. Earth system modelling, planning for sustainable development, and understanding how LULC affects surface radiation balance, temperature, ecology, water flow, and water permeability are all crucial for maintaining sustainable growth and stability of human civilization (Avila *et al.,* 2012; Chang *et al.,* 2018; Ebenezer *et al.,* 2023; Mahmood *et al*., 2014). Although LULC uses a variety of words, land use relates to the physical characteristics of the land, while land cover refers to how people use the land for economic and social purposes (Alikhanov *et al.*, 2020; Kesaulija *et al.,* 2023; Secretariat of the World Meteorological Organization, 2003). The phrase "land cover classification" is defined by the United Nations System of Environmental-Economic Accounting (UN-SEEA) as "observed physical and biological land cover of the Earth's surface and included natural vegetation and abiotic (non-living) surfaces" (UN, 2019). LULC and the climate are interdependent, and each can have an effect on the other as a result of climate change (Gogoi *et al.,* 2019; Kayet *et al.,* 2016). Numerous studies indicate that almost half of the ice-free land area has been modified by humans (Barnosky *et al.,* 2014). Multiple forecasts predict the rise of human population by 2050 to 10 billion people, and therefore, the pressure on the environment and ecosystems will continue to increase (UN, 2019).

Central Asia is one of the regions that is most vulnerable to climate change, according to multiple publications and studies. Its unique landscape, characterized by its temperate deserts and semi-deserts, makes it particularly prone to environmental challenges. The region is predicted to suffer even more from the effects of climate change, worsening the status of natural resources as a result of a projected rise in annual average temperature together with precipitation fluctuations (Alikhanov *et al.*, 2021; IPCC, 2022). Land resources and land cover will be notably affected negatively by climate change and economic pressure due to population growth. The Central and Southern Asia area experienced land degradation at a rate of 28% between 2000 and 2015, which is the second-highest pace globally after Oceania, according to a recent study (Keshri *et al*., 2009). This report states that desertification, deforestation, improper land use, and other anthropogenic factors were mostly to blame for the observed net decrease in the world's natural and semi-natural land cover classifications. Historically, the region's reliance on exporting single agricultural products - such as Kazakhstan's wheat and meat, Uzbekistan's, Tajikistan's, and Turkmenistan's cotton, and Kyrgyzstan's wool - has contributed to its relative lack of development. These vulnerabilities were exacerbated after 1991, following the collapse of the Soviet Union, which led to major economic and institutional upheavals (Lioubimtseva & Henebry, 2009).

Uzbekistan, being a landlocked country located in the center of Central Asia, plays a crucial role in the region's political, economic, and ecological stability. The country's population is 35.6 million people according to the last update (The World Bank, 2022) and will reach approximately 40 million by 2030 (https://kun.uz), putting great pressure on the environment, water resources, and food security. Taking into account that 60 % of the country's territory is covered with deserts and desert zones (FAO, 2011), this pressure puts the country at a very high risk of socio-economic and political vulnerability.

Even though many sources claim the significant LULC change in Uzbekistan, no comprehensive study using remote sensing has been done so far for the whole country. According to Juliev *et al.* (2023), during the last twenty years, only 70 papers were published for the whole Central Asian regions with the keyword “land degradation”, most of them covering the cropland area change. Food and Agriculture Organization of the United Nations annual statistical data on LULC from 1992 to 2017 portrayed an increasingly growing trend in the terrestrial barren land in Uzbekistan during the post-Soviet period (UN, 2019). Karimov *et al.* (2023) analysed land use and land cover change dynamics of the country using remote sensing, literature review, and governmental data from 1990 to 2020. However, the exact methodology of the paper is unclear, and the results do not inspire confidence. (Juliev *et al.,* 2019) analysed the LULC change of the Bostonliq district from 1987 to 2017 with Landsat 5 and 8 satellites. The results of the research show a shift in land cover by increasing the forest area and urban expansion and decreasing bare soil. However, the research uses only two satellite images for the large study period (30 years) and combines soil and rock land classes into one, which limits its robustness. Alikhanov *et al.* (2020) used a similar methodology to detect the LULC change in the Tashkent province from 1992-2018 using four satellite images. The study also discovered significant LULC altercations in the regions. However, it has several limitations: a) the image tiles that were mosaicked for the large area (15K km^2) were obtained for different months (April, May, June) with visible land cover change (vegetation and glaciers); b) authors combined anthropogenic land cover (agriculture) with natural (grasslands, meadows).

Even though the number of research about the LULC change using remote sensing for the country and region is gradually growing, there is still a lack of focus on this crucial topic for Uzbekistan. Aside from that, the existing research analyses past changes without making specific predictions for the future. Remote sensing, combined with machine learning algorithms, can provide not only accurate past examinations but also forecast future land cover shifts based on existing data. Therefore, our research attempts to create a benchmark for future LULC studies for the country by using machine learning tools for both satellite image classification as well as future land cover prediction. LULC detection research without future prediction has limited practical help for the government that manages land policy. On the other hand, accurate depiction of plausible scenarios might help the country avoid the worst and pave the path to the best.

The main goal of this research is to detect and analyze land use and land cover change in Ugam Chatkal National Park, Tashkent province, Uzbekistan, during the post – soviet period of time (1992-2022) using random forest machine learning classification tool and predict plausible land cover changes in the future with CA-Markov machine learning algorithm. The article is divided into four major parts: Introduction (includes the background, literature review, and importance of the study), Research Methods (include the description of the study area, remote sensing and random forest classification description, and CA-Markov model theory with elaborate explanation of three used future scenarios), Results and Discussions (past land cover classification and future three scenarios for the study area, ended with comparison with other studies and limitations of the research) and Conclusion parts.

2. Research Methods

2.1. Study area

Ugam Chatkal National Park is located in the northern part of the Tashkent province, Uzbekistan (Figure 1). The total territory of the park is approximately 668,350 hectares and covers the territory of the Bostanliq and Ohangaron districts of the Tashkent Region. For this research, only the part of the park that covers the Bostanliq district, with a territory of 4,900 km^2, was taken for remote sensing analysis.

The climate of the region is temperate continental, with hot summers and fairly cold winters. The average annual temperature is +15° C. The average January temperature is -9° C, and the average July temperature is +21° C. The absolute minimum temperature was –26° C, and the absolute temperature maximum was +46° C. On average, 500–600 mm of rainfall per year falls on the territory of the district (most of the precipitation falls in spring and autumn). The growing season lasts 210–215 days (Alikhanov *et al.,* 2021).

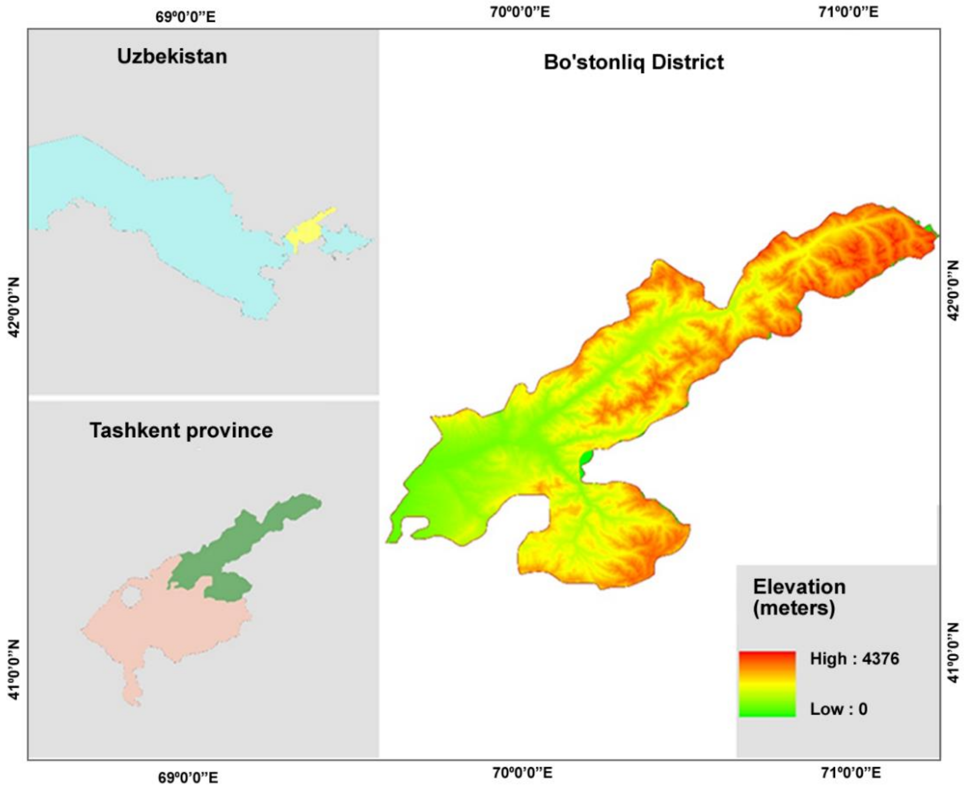

Figure 1. Bo'stonliq district covers 90% of Ugam Chatkal National Park.

The Bostanliq district's terrain is somewhat monotonous and consists primarily of hills, mountains, and high mountains. Except for the northern section, where there are only high mountains, lowlands are common across the western and southern parts of the area. Mountain ranges cover almost the whole area where they are found, including the eastern Tien Shan, the Karzhantau Ridge, the Pskem Mountains, the Ugam Ridge, and the Chatkal Ridge. In accordance, the district's heights rise from west to east and from south to north. The region's southern and western regions are typically 1000 meters above sea level. The remainder of the area, where highlands predominate, is situated somewhere between 1,200 and 4,000 meters above sea level. The Adelung Pskem ridge's top, which reaches 4301 meters above sea level, is the highest point in the vicinity. The mountain's second-highest summit, Beshtor, measures 4299 meters and is another peak of the Pskem ridge. Several high mountains and peaks in the area are between 1,000 and 4,000 meters above sea level, in addition to the peaks and mountains mentioned above. Car routes traverse numerous moderately tall mountains (Petrov *et al.,* 2017).

2.2. Remote sensing

For the temporal LULC classification of Ugam Chatkal National Park, we used atmospherically corrected low-cloud cover Landsat 5 TM and Landsat 8 OLI satellite images from the Google Earth Engine platform. Years for image classification for the study (1993, 2003,2013, and 2022) were selected based on quality, decade, and availability in the GEE image collections. For correct and accurate classification, it was decided to choose May for all classification years. During this period, UCHNP witnessed the peak of its vegetation period, but significant glacier cover remains. In general, more than 600 samples were collected for four images (approximately 150 samples) for the image classification. Some classes required a higher number of samples for correct detection, such as the urban land class, because of its similarity with rocks and bare land. Other land cover classes, like water, required much less samples. Meanwhile, the agriculture land cover class was delineated manually using Google Earth software because this class has a similar spectral signature either with bare land (if the field is harvested), with rangeland (at the beginning of the vegetation stage) or with tree cover (at the peak of the biomass).

Figure 2. Images represent examples of each class of the study area: a) tree cover; b) rocks; c) water ; d) bare land ; e) urban ; f) agriculture ; g) glaciers; h) rangeland.

In the outcome, we divided the images into eight classes: agriculture, water, glaciers, rangelands, tree cover, bare land, urban, and rocks (Figure 2). If the classification results were poor (with lots of incorrect pixel classes), additional samples were added to the collection feature until sufficient classification accuracy was reached. Since the images were already atmospherically corrected, high classification accuracy was attained for all images (Table 1).

Random Forests are collections of classifiers that resemble trees, and they employ bagging's enhanced form of bootstrapping. In other words, they can be seen as an advancement above bagging. In terms of accuracy, it has been demonstrated that Random Forests are equivalent to boosting but without boosting's disadvantages (Sales *et al.,* 2022). Additionally, the Random Forests use significantly less processing power than boosting (Belgiu & Drăguţ, 2016). Multiple decision trees are built using various randomly selected subsets of the data and features in a random forest classification. In deciding how to categorize the data, each decision tree acts as an expert (Belgiu & Drăguţ, 2016; Breiman, 2001).

The Random Forests algorithm was used by (Ham *et al.,* 2005) to classify hyperspectral remote sensing data. Their strategy is put into practice within a multiclassifier system set up in a binary hierarchy. For a hyperspectral data collection with little training data, the experimental findings in the research are decent. Jamali *et al.* (2023) used random forest classification to determine the urban sprawl and land use changes in Iran. The result showed that the combination of systematic points and random forest classification gives high-accuracy results.

In our study, to classify accurately each year and each class, many samples were collected for the study area (Table 1). Collecting samples, classification, and accuracy assessment of the classification was performed in the Google Earth Engine platform. Map presentation and legend-making were finished using ESRI ArcGIS 10.8 software.

Kappa index is utilized to gauge the accuracy and agreement between the classification map derived from remote sensing and the reference data. This index is determined by looking at the major diagonals for direct agreement and considering the row and column totals to assess chance agreement. The classification accuracy of each class for each year is shown in Table 1.

Table 1. Land cover classification accuracy.

Class	1993 (%)	2002 (%)	2013 (%)	2022(%)	The overall accuracy of the class
Water	93	92	93	91	92
Glaciers	84	84	85	86	85
Urban	86	84	85	87	85
Agriculture	87	86	88	89	87
Bare land	85	85	85	86	85
Forests	84	84	86	88	85
Rangelands	84	85	85	86	85
Rocks	82	84	85	86	84
The overall accuracy of the year	86	86	87	88	

2.3. Spatial data

Besides Landsat images, which were used for LULC classification for the past 30 years, we used elevation, slope, and road data as indicators that contribute to future land development (Figure 3).

Road data was downloaded from the Open Street Map free source dataset. Only major roads were taken into account. Distance to roads was generated using the Euclidean distance tool in ArcMap 10.8. The maximum distance made up 47 km, mostly located in the northern mountainous part of the region (Figure 4).

A digital elevation model map was downloaded from NASA's earthdata.nasa.gov ASTER satellite library with a 30-meter pixel resolution. The slope map was derived from the elevation map in the ArcMap software tool. The maximum slope of the region equals 82 degrees.

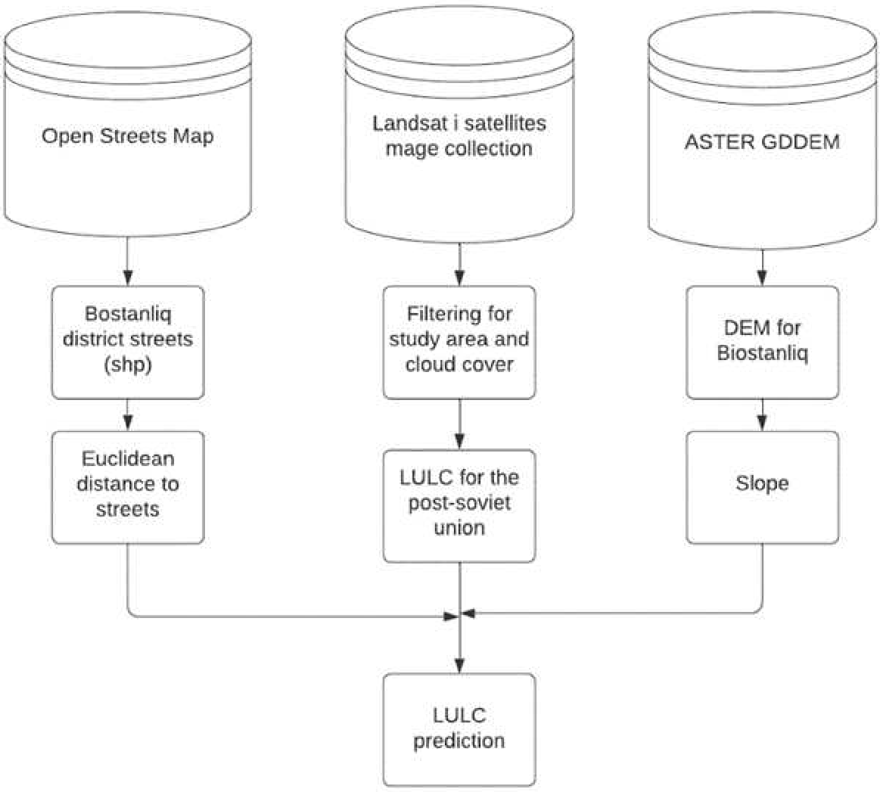

Figure 3. Flow chart of the study.

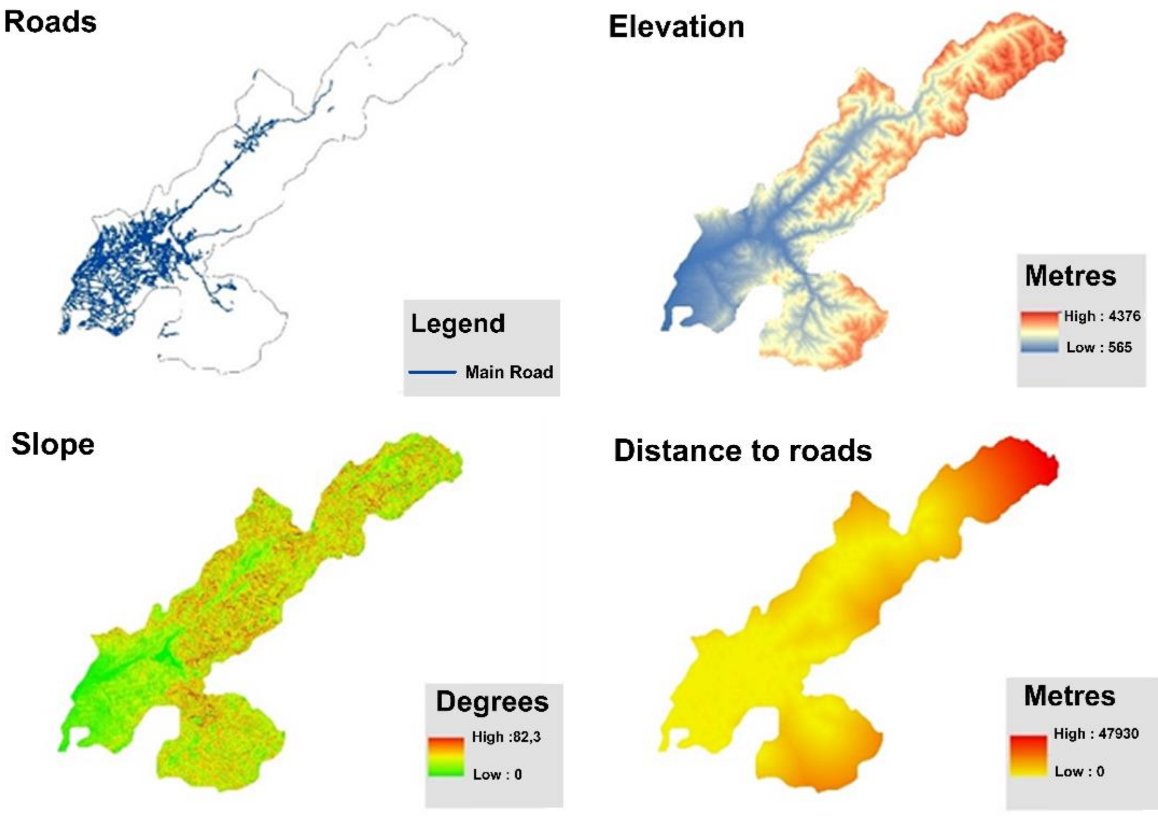

Figure 4. Thematic maps that were used for future LULC prediction.

2.4. CA-Markov model

Various methodologies have been adopted for modelling land-use changes. These include linear and static mathematical models, systems models focusing on stocks and flows, statistical models like regression, cellular models such as Cellular Automata (CA) and Markov Chains, evolutionary models including neural networks, and agent-based models. Often, these different approaches are integrated to develop a hybrid model, leveraging the strengths of each method (Subedi *et al.,* 2013).

The CA-Markov model is an advanced tool that integrates cellular automata, Markov chain analysis, and multi-criteria and multi-objective land allocation techniques to forecast land cover changes over time. This model enhances the traditional Markov model by incorporating spatial contiguity and potential spatial transitions within a specific area over a given period. In the TerrSet 2020 software, the CA-Markov module is utilized to create matrices for transition probability and transition area. A transition probability matrix is generated through the cross-tabulation of two land-use images from different times, determining the likelihood of each pixel's transition from one land-use class to another within that timeframe (Subedi *et al.,* 2013). When integrated with additional modelling approaches, the CA-Markov model significantly enhances the simulation of complex land use systems, offering both increased accuracy and more effective simulation capabilities (Zhang *et al.*, 2023). The Cellular Automata (CA) model is distinct for its spatial discreteness and the specific states of land use, enabling the analysis of spatial distribution and interactions among neighbouring areas. As a discrete mathematical system, the CA model fundamentally comprises five elements: a uniform, regular lattice, a cell, a state assigned to each cell, neighbouring cells, and the set of rules governing the transitions of these states.

The Markov model, in the context of land-use change modelling, is effective because it considers historical states to forecast how a specific variable evolves over time. Its strength lies in its capability to measure not just the different transitions between types of land use but also the pace at which these changes occur. This makes the Markov model a valuable tool for understanding and predicting land-use dynamics (Sang *et al.,* 2011). The combined use of the Cellular Automata (CA) and Markov model is effective for simulating land-use dynamics. The CA model is adept at depicting spatial position changes, while the Markov transformation matrix is utilized to simulate temporal variations in land use (Zhang *et al.,* 2023). The future LULC was simulated using the following Markov model (Equation 1)

$$S(t+1) = P_{ij} \times S(t) \tag{1}$$

where $S(t)$ and $S(t+1)$ are the system status at time t and $t+1$, respectively, and P_{ij} is the transition probability matrix in a state, which is calculated as Equation 2.

$$\text{Pij} = [P11 \ \cdots \ P1n \ \vdots \ddots \vdots \ Pn1 \ \cdots \ Pnn\ ]$$

$$\left(0 \le P_{ij} < \sum_{j}^{N} = 1\ P_{ij} = 1, (i, j = 1, 2, \ldots \ldots n)\right) \tag{2}$$

The CA model has been utilized to describe the overall complex, self-organizing system, focusing on the behaviours of individual cells and their interactions with neighbouring cells. In simulating land-use changes, it operates under the assumption that areas are more likely to transform into a certain type of land use when similar land use is present in the vicinity. This reflects the model's emphasis on the influence of local conditions and neighbouring influences on land-use dynamics (Fu *et al.,* 2018; Wang *et al.,* 2022).

The model is formulated as Equation 3.

$$S^{t+1} = f(S^{t}_{i\,j}\, \Omega_i jt, V) \tag{3}$$

In this model, the states of a cell at row i and column j during the start (t) and end (t + 1) of the simulation are denoted as Sti,j and St+1i,j, respectively. The model factors in the neighbouring cells' states (Ωti,j) at time t, a set of suitability factors (V), and applies a transition law (f) to determine the state changes (Wolfram, 1984).

The first step was to identify transition potentials between land use maps with a machine-learning algorithm. We used maps from 2002 to 2013 to identify the patterns of land use and land cover change during this decade. TerrSet allows to incorporation of a maximum of nine classes of transition sub-models, therefore the most important sub-models were taken into the learning: water to bare land, glaciers to rangelands, glaciers to rocks, rangelands to forests, rangelands to bare land, bare land to forests, rocks to forests. For the transition sub-model structure, we included five important layers that impact and help to identify land cover transition, namely elevation (static), and slope (static). Distance to roads (static), rangelands to all (LULC for 2002 and 2013 were analyzed, and rangeland transition to all other land classes was analyzed as being the most important ecosystem in the study area), and change maps were included.

For machine learning, we used 10000 iterations with 800 pixels for each class (50 % for training and 50 % for testing). After the learning process, the accuracy rate of the CA-Markov model made up 78 %. The learned data was applied to create the 2022 LULC map and validated with the classified 2022 map. The overall accuracy of the predicted map made up 83 %, making the smallest accuracy prediction for glaciers (75 %) and urban (56 %) land cover classes. The same model was applied to predict LULC maps for 2035, 2045, 2055, and 2065 (hard, bad, and soft predictions).

In TerrSet, land cover prediction can be approached in two primary ways: hard and soft classification. Hard classification, also known as crisp classification, assigns each pixel in a satellite image to one and only one land cover class. It operates on the principle of maximum likelihood, where each pixel's spectral signature is compared with the spectral signature of known classes, and the pixel is assigned to the class with which it has the highest probability of association. The output is a categorical map with distinct boundaries between land cover types without any ambiguity or overlap. This method does not account for mixed pixels, which are pixels that contain more than one land cover type within the area that the pixel represents. Hard classification is often used when a clear, definitive categorization is needed, and the spatial resolution of the imagery is high enough to minimize the presence of mixed pixels (Eastman & He, 2020). Soft classification, also known as fuzzy classification, recognizes that pixels can represent mixed ground cover types, especially in coarse-resolution images where a single pixel can cover large areas on the ground. Instead of assigning a single class to a pixel, soft classification assigns probabilities or membership values to each class. So a pixel might be 70% forest, 20% grassland, and 10% urban, for example. This approach is particularly useful in complex landscapes where land cover types are not clearly separable or when dealing with images with mixed pixels. The output is usually a set of probability maps, one for each land cover class, indicating the likelihood of each pixel belonging to each of the possible classes. Soft classification is more nuanced and can be more accurate in terms of representing reality on the ground, but it is also more complex to interpret and use in further analyses (Bradley *et al.,* 2017).

Besides the aforementioned scenarios, that are embedded into the TerrSet software, users are able to create their own scenarios manually changing the probability transition matrix in the change prediction. Initially, the matrix values are computed by the software using CA-Markov machine learning algorithm during the learning of transition potentials for the previous years (in our case 2002 and 2013). However, the transition potentials show the probability values for one decade, whereas in the future the land cover change might witness significant changes due to external impact. There are two major factors that impact LULC: anthropogenic (deforestation due to tree cutting, overgrazing due to excessive grazing, intensive agricultural activity, and rapid urbanization) and climatic factors (temperature rise, glaciers melting, and precipitation decline). In our "bad scenario," we mainly used anthropogenic impact to anticipate land cover change in the region in the future. The main reason behind this was the government's active policy to involve investors for the Bostonliq region, raise agricultural activity to maintain the growing population of Tashkent city (that is supplied with meat and other products from the study area), and a growing number of cattle to graze on the UCHNP rangelands. Therefore, we increased the probability values for urban and agricultural in the transition matrix.

3. Results and Discussion

As we can see from Table 2 and Figure 5, the LULC of the study region fluctuated during the post-soviet period. The biggest change we can observe is the glaciers' land class, which had a dramatic decline in the area during the last twenty years (from 2125 km^2 to 1330 km^2). Many researchers have noticed that mountain glaciers in the Bo'stanliq district are melting year by year.

The area under water class sees a significant decline from 1993 to 2002, after which it stabilizes. There is a slight increase in 2022, suggesting a minor recovery or expansion of water bodies. The same pattern can be observed for the rangelands. The area of rangelands decreases marginally from 1993 to 2013. However, there is an upward trend in 2022, suggesting an increase or recovery in rangeland areas in recent years.

Initially, there was a sharp decline in tree cover from 1993 to 2002. However, from 2002 onwards, there was a substantial increase, with the area in 2022 surpassing all previous years. This condition indicates significant afforestation or natural tree growth in recent years. This afforestation can be explained by the melting of glaciers in high-altitude areas, which were covered with deciduous trees (at a lower altitude) and rocks.

The area covered by agriculture remains stable throughout the study period, slightly decreasing to 65 km^2 in 2013, which may be related to either low agricultural activity during that period or some inaccuracy in land cover classification. The total territory of the urban land cover class made up 50 km^2 in 1993. In 2002, the area declined by 13 km^2 (which may be due to the deconstruction of urban areas or some inaccuracy in land classification). Afterwards, it started to rise to 53 km^2 in 2013 and experienced a dramatic increase in 2022 (90 km^2), which shows the urbanization trend for the study region (Table 2, Figure 5).

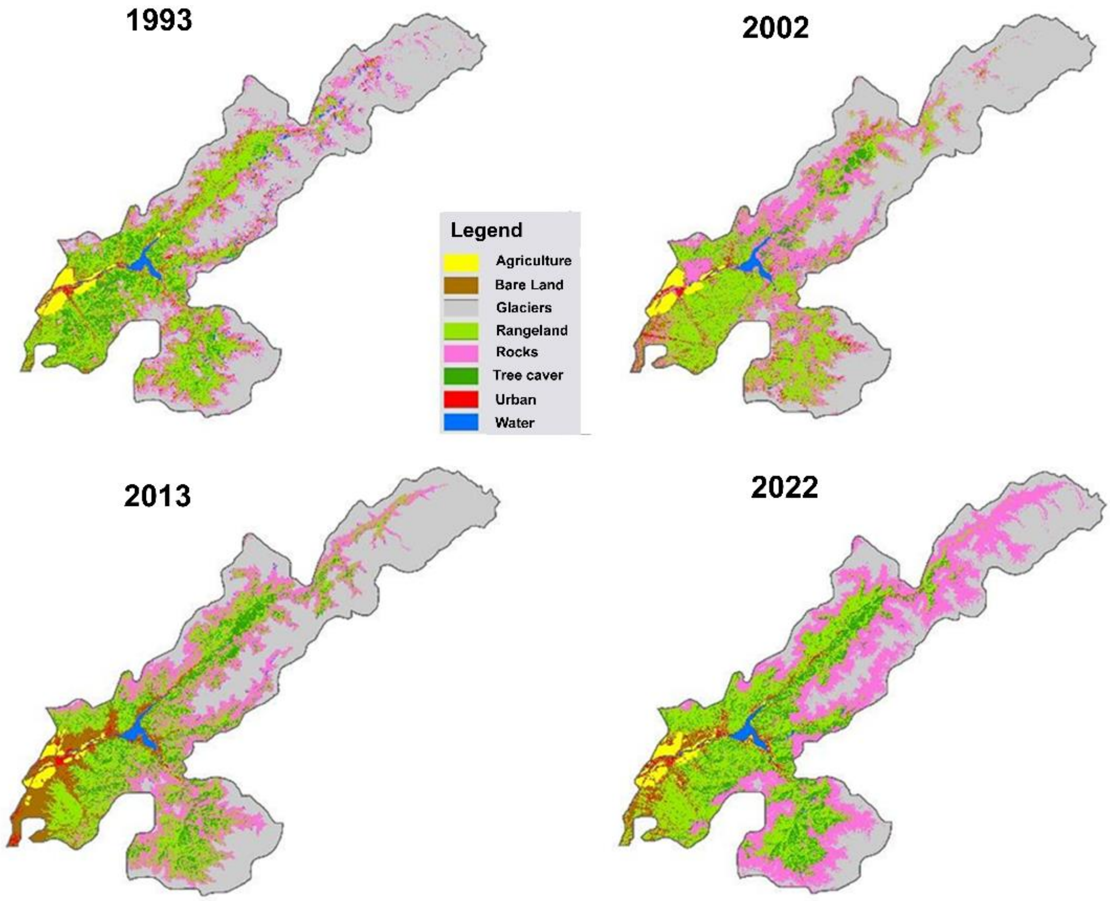

Figure 5. Land use and land cover change of Bostonliq district (Ugam Chatkal National Park) during the post-soviet period.

Table 2. LULC change during the post-soviet period.

Class	1993	2002	2013	2022
Agriculture	77	76	65	73
Water	78	52	52	55
Glaciers	2105	2125	1813	1334
Rangelands	1259	1174	1148	1333
Tree cover	327	164	414	450
Bare land	248	207	343	249
Urban	50	37	53	90
Rocks	834	1139	1093	1390

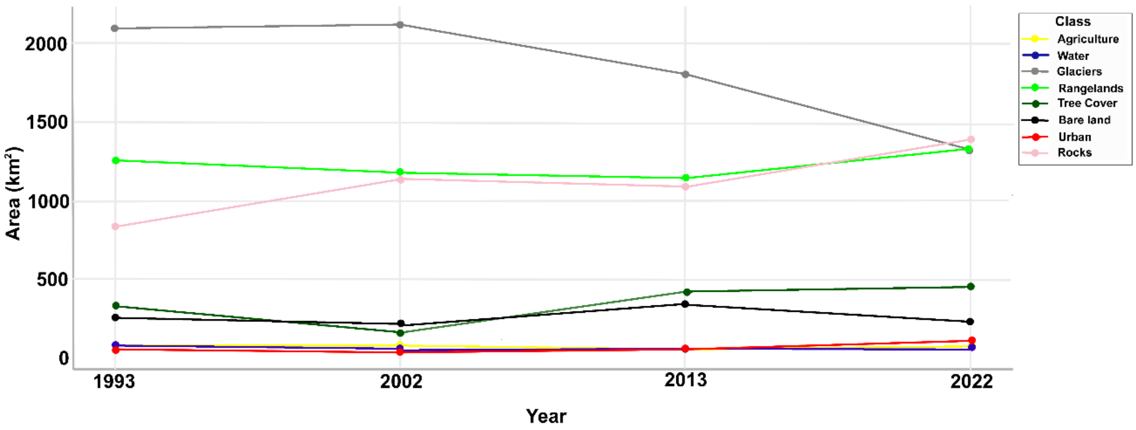

Figure 6. LULC in UCHNP during the post-soviet period (1993-2022).

Rocks land class experienced a gradual increase during the study period, starting from 834 km^2 in 1993, increasing to 1139 km^2 after a decade (300 km^2), slightly declining after a decade, and then rising again in 2022 until 1394 km^2. In general, during the post-soviet period of time rocks land class increased by 167%, which might be due to glaciers melting.

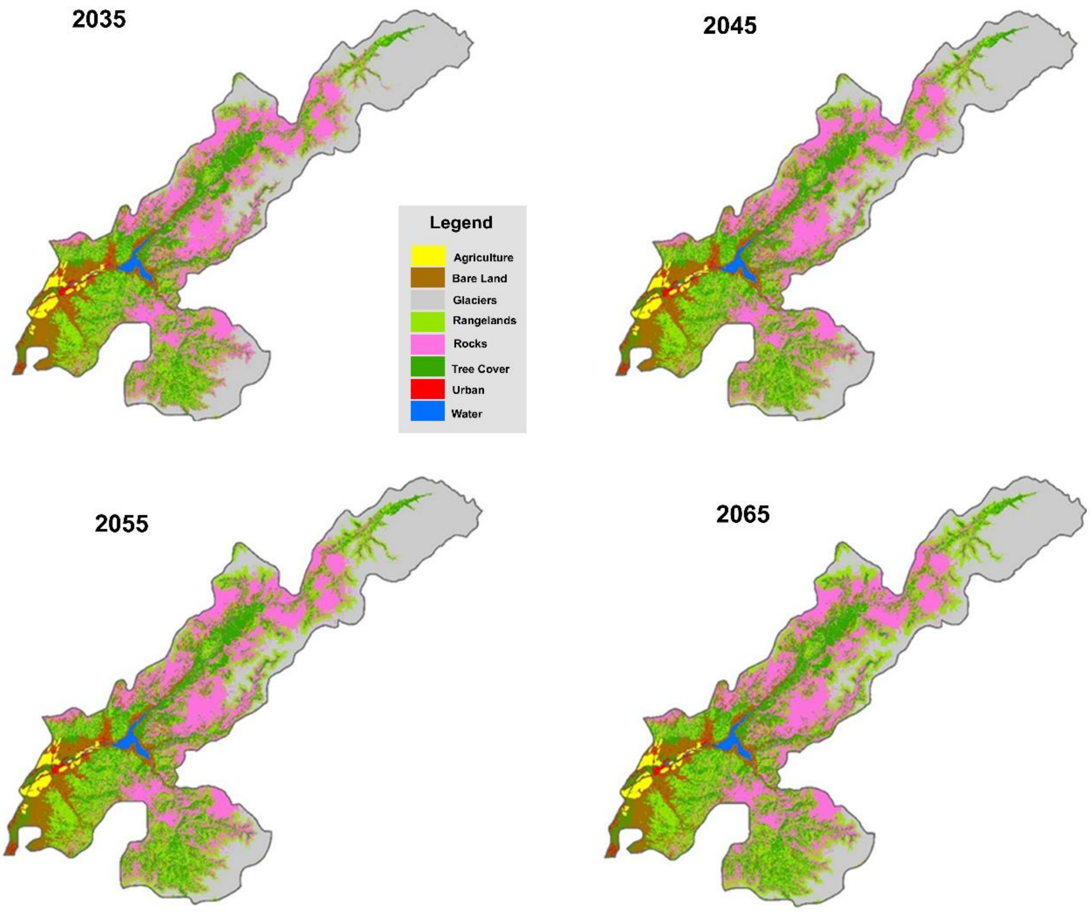

Figure 7. Future land use and land cover change in the region (soft prediction).

Agriculture: Predicted to slightly decrease from 62 km² in 2035 to 60 km² in 2065, suggesting a marginal reduction in agricultural land. A steady decline is observed in water bodies, going from 51 km² in 2035 to 48 km² in 2065. This could indicate the impact of climate change on water resources or increased water utilization in the future. At the same time, a significant reduction in glacier areas is projected, from 1323 km² in 2035 to 1055 km² in 2065. This trend is likely a direct consequence of global warming and the rise in regional average temperature.

When it comes to rangelands, there is an expected increase from 897 km² in 2035 to 1136 km² in 2065. This can be due to several reasons: former water bodies will turn into grazing lands, some areas of former glaciers will become mixed pastures and trees, or some bare land areas will witness the growth of sparse vegetation.

Forested areas are set to grow gradually from 835 km² in 2035 to 903 km² in 2065, indicating positive outcomes from reforestation initiatives or natural forest regeneration. However, the major reason behind this will be the melting of glaciers at lower altitudes due to rising temperatures that make it possible for evergreen or deciduous trees to grow. Meanwhile, a slight decrease in bare land areas is anticipated, from 443 km² in 2035 to 432 km² in 2065, possibly due to land development or natural transformations.

Urban: An increase in urban areas is forecasted, from 55.0 km² in 2035 to 60.0 km² in 2065, suggesting urban expansion. Last but not least, a minor decline is projected in rocky areas, from 1312 km² in 2035 to 1290 km² in 2065, potentially due to erosion or land use changes.

Table 3. Future scope of LULC for the next thirty years in the region according to soft prediction (in km^2).

Class	2035	2045	2055	2065
Agriculture	62	62	61	60
Water	51	50	49	48
Glaciers	1323	1208	1122	1055
Rangelands	897	986	1067	1136
Tree cover	835	874	893	903
Bare land	443	437	434	432
Urban	55	57	59	60
Rocks	1312	1306	1296	1290

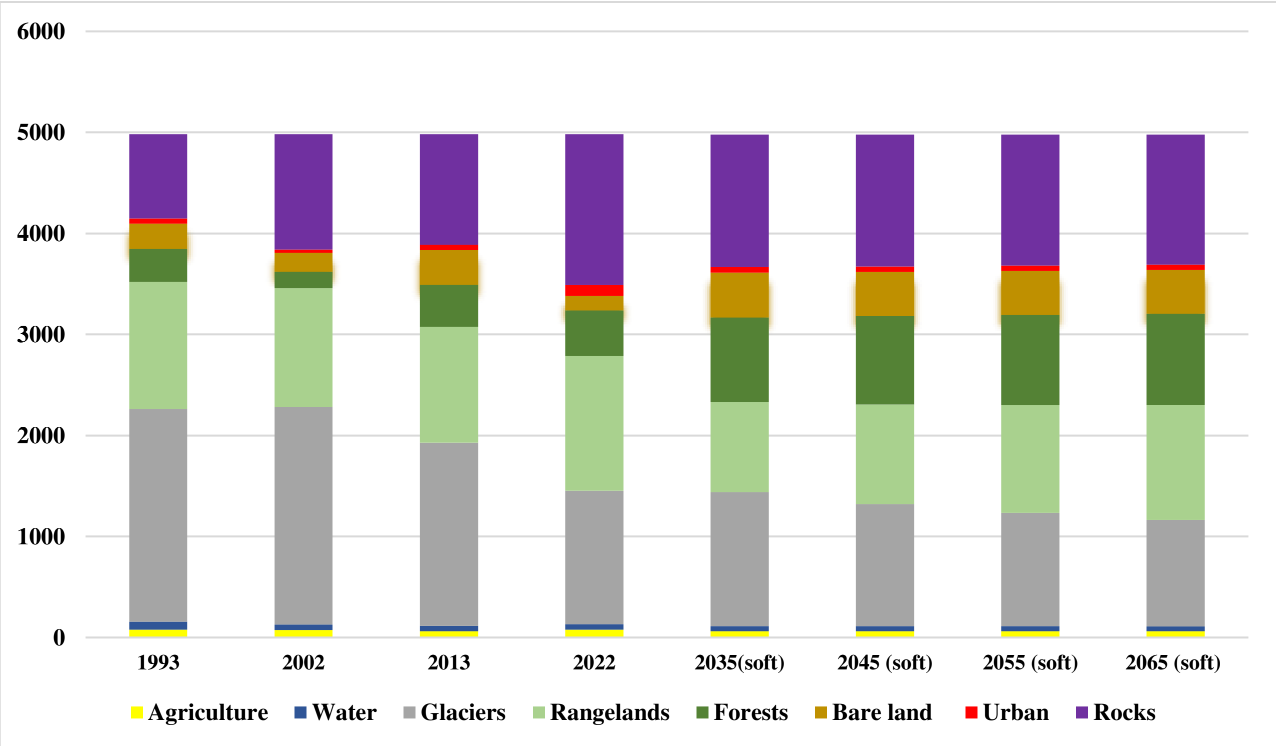

Figure 8. Bar chart of LULC for the past and soft-prediction future with CA-Markov model.

Figures 9 and 10 and Table 4 show the LULC prediction for the study area according to "hard prediction". Agriculture shows a slight decrease in area, suggesting marginal changes in agricultural practices. Water bodies and glaciers across both types of prediction indicate a general trend of reduction, likely a direct consequence of climate change and its impacts on natural resources. Interestingly, glaciers in hard prediction exhibit fluctuating measurements, potentially reflecting variable climatic influences over the years.

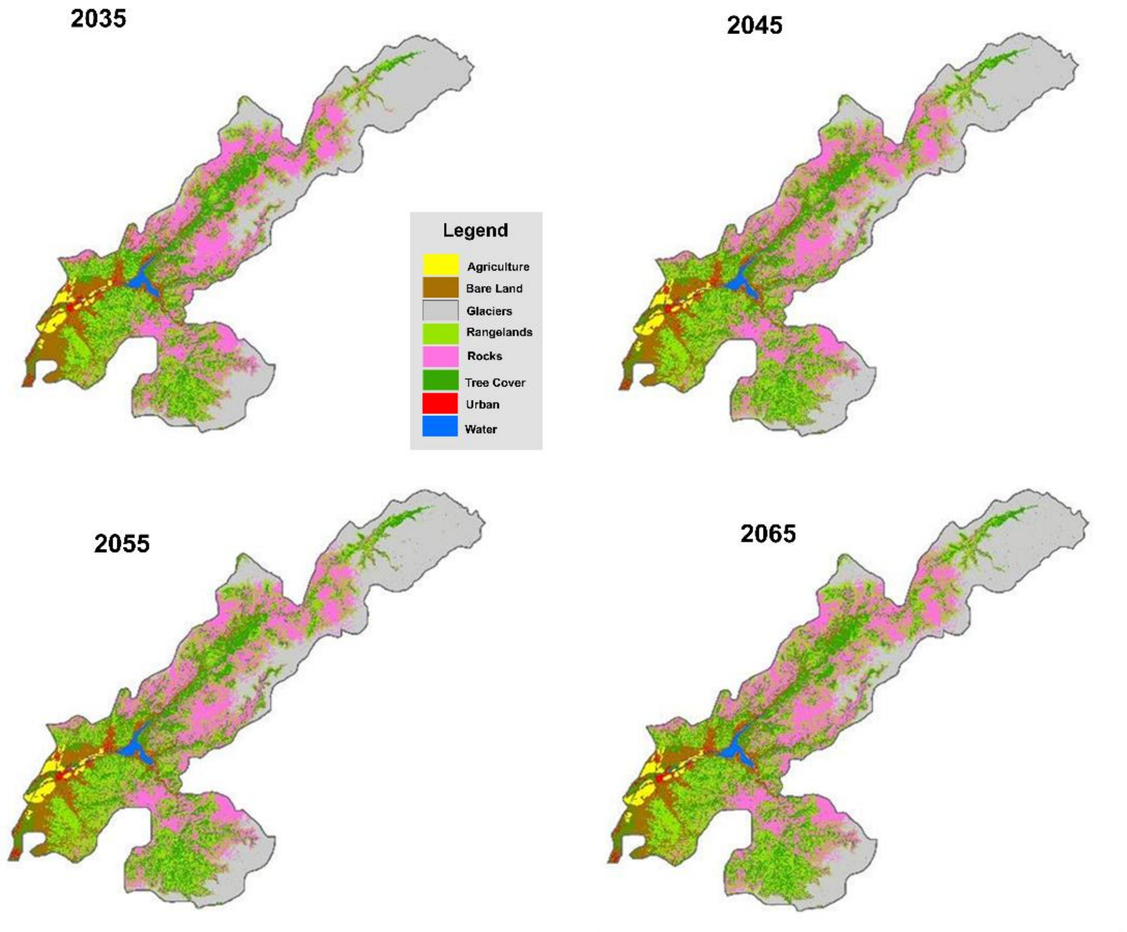

Figure 9. Future land use and land cover change in the region (hard prediction).

In contrast, both tree cover and urban areas are consistently projected to increase, indicating ongoing urban expansion alongside positive reforestation efforts or natural forest growth. Rangelands and bare land exhibit varying trends, with rangelands initially declining before increasing, possibly due to changing land use or conservation policies. The gradual decrease in rocky areas suggests potential land development or natural transformations. Collectively, these predictions underscore the dynamic interplay between human activities and natural processes, highlighting the need for sustainable land management and environmental conservation strategies in the face of evolving global and regional challenges.

Table 4. The future scope of LULC for the next thirty years in the region is according to hard prediction (in km^2).

Class	2035	2045	2055	2065
Agriculture	61	61	61	60
Water	51	50	49	48
Glaciers	1320	1205	1212	1165
Rangelands	1320	1027	1102	1171
Tree cover	834	872	887	895
Bare land	442	436	430	427
Urban	53	54	55	56
Rocks	1309	1302	1286	1276

To highlight the major differences between the "soft" type predictions and the "hard" type predictions, we can analyze how each type approaches the projection of future changes in various land cover classes. The "soft" predictions might represent more conservative or gradual changes, while "hard" predictions could indicate more drastic or immediate changes.

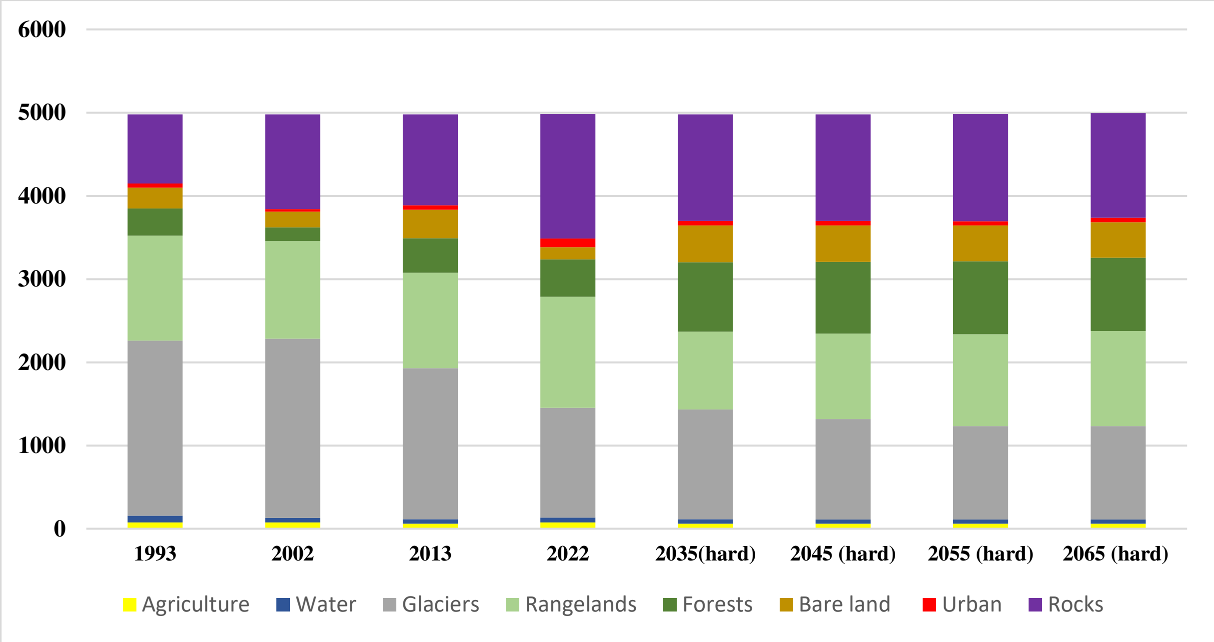

Figure 10. Bar chart of LULC for the past and hard prediction future with CA-Markov model

The "soft" predictions and the "hard" predictions provide distinct outlooks on the future state of various land cover classes, each encapsulating different degrees of change over time. In the case of agriculture, "soft" predictions suggest a stable trend with a minor decrease towards the end, whereas "hard" predictions indicate a more pronounced and earlier reduction in agricultural areas. For water bodies, both prediction types show a decline, but it is slightly more accelerated in the "hard" type, hinting at a faster depletion of water resources under more drastic scenarios. Glaciers, interestingly, display more variability in "hard" prediction, with an interim increase before a decline, suggesting that the "hard" predictions account for more fluctuating climatic impacts on glaciers.

In terms of rangelands, urban areas, and tree cover, "soft" predicts a consistent expansion, in contrast to "hard" where rangelands initially decrease then increase, reflecting a more dynamic interplay of adverse effects and subsequent recovery in the "hard" scenario. Urban expansion and forest growth are also more aggressive in "hard", indicating rapid changes in land use patterns. Bare land and rocks show a more pronounced decrease in "hard", alluding to faster land development and natural transformations. Overall, the "hard" predictions depict a landscape of more immediate and dynamic changes, suggesting a scenario where environmental and human factors induce quicker transformations in land use and land cover.

The last scenario that is considered in this research is “a bad scenario”, which incorporates rapid urbanization and the rise of agricultural activity in the region (Figures 11 and 12 and Table 5). The area covered with agriculture will cover 63 km^2 of the study area, which is not significantly different from the previous two scenarios. However, during the next three decades, the class starts to soar, reaching 222 and 286 km^2 in 2055 and 2065 respectively. The new areas conquered by agricultural expansion, according to Figure 11, will be lowlands, rangelands, bare lands, and areas along the river streams.

Another class that will witness rapid expansion due to human activity is urban areas. According to the “bad” scenario prediction, in 2035, the total area covered by the class will reach 85 km^2, which is much higher than “hard” and “soft” prediction scenarios. In 2045, the urban area is predicted to cover 120 km^2 already, almost doubling within a decade to 217 km^2 and reaching 415 km^2 in 2065 (Table 5). The main areas of urban expansion will be lowland areas, previously covered with rangelands, trees, and bare land, as well as the area across the Charvak water reservoir (Figure 11).

Among land cover classes that will experience a significant decline in the area are glaciers (from 1383 km^2 in 2035 to 1172 km^2), as well as rangeland ecosystems (from 995 km^2 in 2035 to 635 km^2 in 2065). Meanwhile, the tree cover land class will witness fluctuations, rising to 250 km^2 in 2045, then falling to 151 km^2 again after ten years, continuing with rising to 248 km^2 in 2065.

This instability might be connected to the dynamic interplay among other land cover classes that have dramatic altercations.

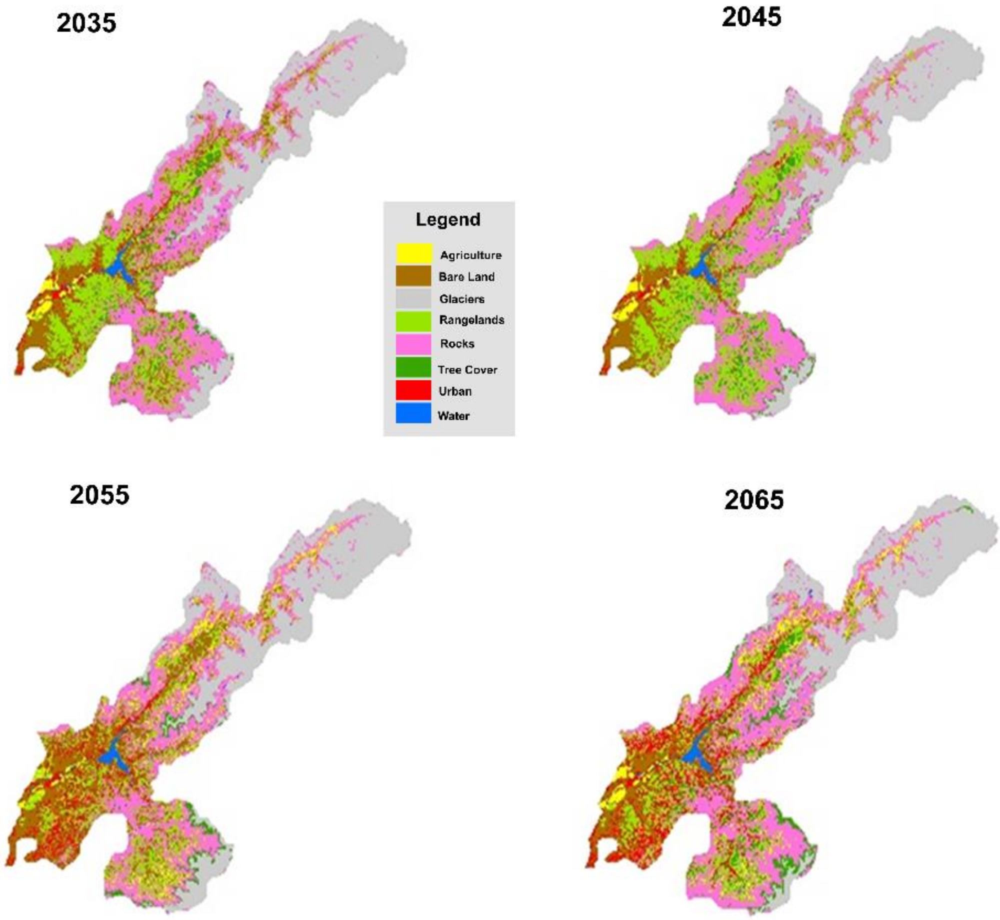

Figure 11. Future land use and land cover change according to the “bad” prediction scenario.

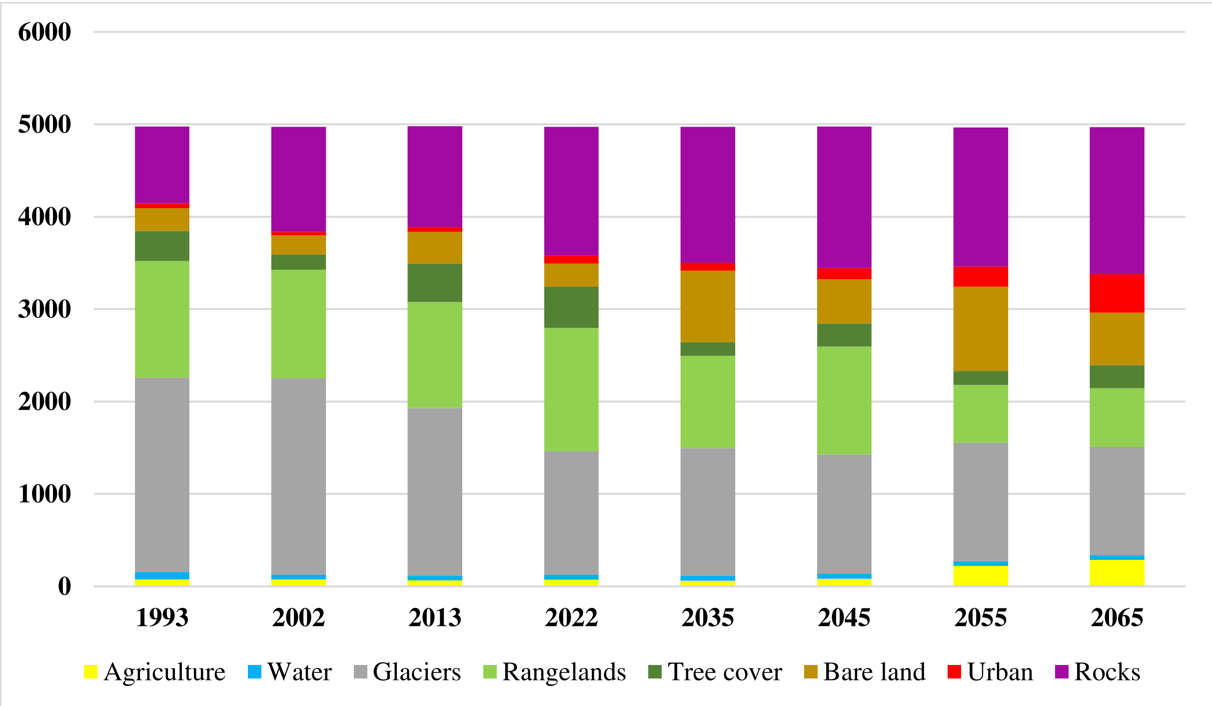

Figure 12. Bar chart of LULC for the past and bad prediction future with the CA-Markov model.

Table 5. The future scope of LULC for the next thirty years in the region is according to a "bad" prediction (in km^2).

Class	2035	2045	2055	2065
Agriculture	63	81	222	286
Water	52	52	52	52
Glaciers	1383	1293	1281	1172
Rangelands	995	1170	625	635
Tree cover	150	250	151	248
Bare land	774	477	913	570
Urban	85	120	217	415
Rocks	1472	1535	1505	1591

Our findings have similarities with Juliev *et al.* (2019), who also classified the land cover of the Bostanliq district for the years 1987 and 2017. According to their research, the study area experienced afforestation (from 1500 km^2 to 1805 km^2). However, their article does not include the rangeland land class. Probably, some areas of meadows and pastures with small levels of tree cover were classified by them as "forests", whereas we included these areas into rangeland land cover because they are used for grazing. Another significant difference between our results and Julievs' findings is the total agricultural area. If, in our case, the cropland area for the study region was found to be close to 70 km2 for the whole post-Soviet period, Juliev's cropland area was 655 km^2 for both years. This huge area for the agricultural land cover class seems impossible because Bostonliq district is not famous for its agricultural production due to several reasons: a) the district is considered a national park; b) the district territory (especially in the north) are mountains and hills; c) the park is mostly used as grazing land. Such a large area assigned to the agriculture land class by Juliev *et al.* (2023) might be because the class is mixed with rangelands with low or moderate biomass. One of the main challenges the remote sensing specialists face during the classification is discerning between the dense tree cover, pastures, and agricultural lands. At the beginning of the vegetation period, agriculture has a similar spectral signature as rangelands (pastures, meadows, scrublands), whereas at the peak of the vegetation, they can be classified as forests (with high biomass). The results are the same whether specialists use NDVI or classification. Therefore, in our study, we deliberately delineated agricultural plots beforehand with Google Earth for each study year, converted them into pixels, and then merged with LULC images. Hence, our results are more robust than Juluev's findings.

Nevertheless, our research has its own limitations. The major limitation is the region's future land use and land cover prediction. LULC change is a very complex process that involves both human activity and climate change. Human activity mainly incorporates population growth and governmental policy. The population growth can be due to both natural growth and immigration. According to the last census (2021), the total population of the Bostonliq district is only 171000 people, but this might be an underestimation because, during the grazing period, many pastoralists live in rangelands and herd their livestock. Moreover, many people from the capital have country houses where they live during summer time. In addition, the region has witnessed large construction objects during the last five years, both real estate and recreation. The government's policy is to involve investors in the region, which might lead to population growth. Likewise, the government's policy depends on the protection of trees and natural ecosystems, as well as setting quotas on grazing periods and livestock numbers for pastoralists. Therefore, it is very hard to predict LULC change in the future for our study area. Besides that, the future of the regional and global climate is unpredictable and will depend on global CO_2 emissions. For these reasons, all three future scenarios must be considered as among many other plausible ones the region might face in the next 40 years.

4. Conclusion

In conclusion, this study on land use and land cover (LULC) changes in Ugam Chatkal National Park, Uzbekistan, utilizing CA-Markov and Random Forest machine learning algorithms, provides significant insights into the environmental changes over a 30-year period from 1993 to 2022. The analysis reveals the impact of climate change and human activities on the park's ecosystem. The research highlights the effectiveness of integrating remote sensing data with advanced machine learning techniques for accurate LULC classification and future predictions. This approach not only allows for a detailed understanding of past changes but also aids in making both probabilistic ('soft') and definitive ('hard') forecasts for future LULC scenarios, as well as ('bad') prediction based on user's manually assigned parameters for transition probabilities.

These findings are crucial for policymakers and environmental managers, offering a foundation for developing informed conservation strategies. The study emphasizes the need for sustainable development practices to mitigate adverse impacts on these valuable natural resources. The predictive models used in this research can serve as a template for similar studies in other regions, enhancing our capability to manage and protect natural landscapes amid growing environmental concerns.

The research underscores the dynamic interplay between natural and anthropogenic factors in shaping land cover, stressing the importance of continuous monitoring and adaptive management in conservation efforts. The detailed analysis of LULC changes in Ugam Chatkal National Park serves as a vital resource for understanding the broader implications of environmental change in Central Asia, and it provides a model for addressing similar challenges globally.

Nevertheless, the findings of the research, especially the future predictions should be considered with caution due to the impossibility of validation and verification. For future articles, the future land use and land cover scenarios must be matched with the universally acknowledged type of scenarios (Business-as-usual, Sustainability Scenario, Socioeconomic Development Scenario, Climate Change Scenario and Technological Advancements Scenario) used by international organizations, such as FAO, The Nature Conservancy and World Resources Institute.

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Author Contributions

Conceptualization: Alikhanov, B; Pulatov, B.;**methodology**: Alikhanov, B; Pulatov, B.;**investigation**: Alikhanov, B; **writing—original draft preparation**: Alikhanov, B; **writing—review and editing**: Alikhanov, B, Samiev, L.; **visualization**: Alikhanov, B. Authors have read and agreed to the published version of the manuscript.

Conflict of interest

Authors declare that they have no conflicts of interest.

Data availability

Data is available upon Request.

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