FORUM GEOGRAFI
ISSN: 0852-0682 | E-ISSN: 2460-3945

Research article

Vegetation Cover Change in Ugam Chatkal National Park, Uzbekistan, in Relation to Climate Variables During the Post-Soviet Period (1991-2022)

Bokhir Alikhanov[1,*], Bakhtiyor Pulatov[1], Luqmon Samiev[1,2]

[1] Research Institute of Environment and Nature Conservation Technologies, Ministry of Ecology, Environmental protection and Climate change, Tashkent 100043, Uzbekistan
[2] Tashkent Institute of Irrigation and Agricultural Mechanisation Engineers" National Research University, Tashkent 100000., Uzbekistan

[*] Correspondence: alihanovbahir@gmail.com

Citation:

Alikhanov, B., Pulatov , B., & Samiev, L. (2024). Vegetation cover change in Ugam Chatkal National Park, Uzbekistan, in rela-tion to climate variables during the post-Soviet period (1991-2022). Forum Geografi. 38(1), 11-27.

Article history:
Received: 31 December 2023
Revised: 16 January 2024
Accepted: 26 January 2024
Published: 22 March 2024

Abstract

This paper presents a comprehensive study relating to the vegetation cover change in Ugam Chatkal National Park (Uzbekistan) and its relation to climate change during the post-Soviet period (1991-2022). The study utilises remote sensing technology, specifically the Normalised Difference Vegetation Index (NDVI) and the Soil Adjusted Vegetation Index (SAVI), to monitor spatiotemporal changes in vegetation. Landsat satellite imagery and meteorological data, including temperature and precipitation records form the basis of the analysis. The research aims to understand the impact of climatic factors, such as air temperature, soil temperature, and precipitation on vegetation cover. Statistical methods, such as Pearson's correlation analysis, are employed to determine the strength and direction of relationships between these variables. The study reveals that both NDVI and SAVI are strongly correlated with air and soil temperatures, indicating the significant influence of these climatic factors on vegetation health and growth. The findings suggest that changes in vegetation cover in the Ugam Chatkal National Park are closely tied to climate change, with air temperature revealing a substantial correlation with time, indicating a trend toward increasing temperatures. The study also forecasts future climatic and vegetation trends, predicting an increase in air temperature, precipitation, and vegetation cover over the next four decades. In particular, the research highlights the magnitude of monitoring and understanding the complex interactions between climate change and vegetation dynamics, which are crucial for environmental management and regional policy-making.

Keywords: NDVI; SAVI; climate change; future climate prediction; vegetation trends; Boʻstonliq.

1. Introduction

Vegetation is part of various terrestrial ecosystems, from African savanna's and Siberian Tundra's to tropical rainforests and Central Asian steppes. Therefore, it plays an essential role in the different processes and cycles that occur within an ecosystem (Fu *et al*., 2014). Woody vegetation and rangelands are fundamental in regulating local and global climate, energy exchange, carbon cycle, and water circulation (Regmi *et al*., 2020; Sun *et al*., 2021). The vegetation of a natural ecosystem comprises several distinct features. This may include vegetation biomass, greenness, vegetation coverage, and phenological metrics variation, which are important and unbalanced factors (Kalisa *et al*., 2019).

There are two principal reasons a natural ecosystem's vegetation experiences change: anthropogenic and climatic. Anthropogenic factors include overgrazing, deforestation due to the felling of trees, and urbanization, which results in land use and land cover change and the deterioration of vegetation parameters. Precipitation and temperature are the two crucial factors influencing vegetation growth, time, health, and type (Adepoju *et al*., 2019). In addition to precipitation and temperature, other climatic and environmental factors impact the spatiotemporal characteristics of vegetation, such as soil moisture, evapotranspiration, and radiation (Zhao *et al.*, 2019).

Many recent studies indicate that soil moisture is a factor that connects climatic parameters (precipitation and temperature) with NDVI, and therefore, it must not be disregarded (Wang *et al.*, 2003). Additional studies have ascertained that soil moisture is the most crucial environmental variable that directly impacts vegetation growth (Na *et al*., 2021). Most of the previous studies completed by various researchers investigated the impact of the climatic fluctuations associated with vegetation growth and cover, overlooking soil moisture (Hussien *et al*., 2023). However, according to numerous authors, soil moisture plays an essential role in the functioning of all ecosystems as a major abiotic terrestrial parameter (Feng *et al*., 2017; Wang *et al*., 2015).

Remote sensing is the only available technology today that allows the continuous monitoring and detection of spatio-temporal changes over a significant area and for an extended period (Eisfelder *et al*., 2023). NDVI time-series analysis was employed to monitor vegetation cover change in different areas, for instance, agriculture (Momm *et al*., 2020; Tottrup & Rasmussen, 2004) deforestation and the risk assessment of forest fires (Gabban *et al*., 2004; Michael *et al*., 2021; Walker

& Soulard, 2019), as well as desertification and rangeland degradation issues (Helldén & Tottrup, 2008; Paudel & Andersen, 2010; Zhao *et al.*, 2023).

According to several authors (Dech *et al.*, 2021; Eisfelder et al., 2023; Lieberherr & Wunderle, 2018), at least three decades of monitoring is necessary to relate vegetation cover with climate variables. The Landsat series of satellites which are frequently used for this sort of research, provides the highest-resolution satellite images with continuing coverage. Globally, trend analysis – an extremely common tool to investigate vegetation change, has been employed (Dong et al., 2022; Faour *et al.*, 2018; Pouliot *et al.*, 2009; Tian *et al.*, 2015). The studies above examined annual trends, nevertheless, the impact of climate change on vegetation cover can be diverse and vary over space and time.

Vegetation cover change, whether it has an anthropogenic or climatic reason, has a profound impact on many environmental factors. A reduction in vegetation biomass changes the albedo of the land surface, increases local temperature, and also changes evapotranspiration rates, hydrological balance, etc., (Wang *et al*., 2003). Therefore, monitoring the vegetation of a region is considered a key factor in predicting environmental changes.

The projections regarding how drylands might react to global climate change remain uncertain. This is notably true in the Central Asian countries that were once part of the former Soviet Union (USSR), where the potential effects of climate change are particularly ambiguous (Lioubimtseva & Henebry, 2009). Climate change could significantly affect ecosystems, agriculture, and water supplies, besides the health and well-being of people throughout Eurasia. The transitional economies of the Central Asian republics are especially at risk from ongoing and future environmental shifts. This vulnerability results from their geographic characteristics and the various political, economic, and institutional transformations they have experienced since 1991.

Central Asia is exceptionally susceptible to climate and environmental challenges caused by its specific geographical features, which include temperate deserts and semi-deserts. This vulnerability is compounded by its historical focus on exporting agricultural monocultures, such as wheat and meat in Kazakhstan, cotton in Uzbekistan, Tajikistan and Turkmenistan, and wool in Kyrgyzstan, leading to relative underdevelopment. The situation deteriorated after 1991 due to the significant economic and institutional disruptions that followed the dissolution of the USSR (Lioubimtseva & Henebry, 2009).

Paleoclimate and archaeological evidence proposes that Central Asia's arid and semi-arid regions have endured numerous climate fluctuations, which could be similar to those predicted to occur during future climate change. According to reconstructions from the early to mid-Holocene, Central Asia's arid areas could become wetter due to global warming. This change is expected to result from a southward movement and the possible strengthening of the westerly cyclones (Lioubimtseva *et al.*, 2005). Meteorological records dating back to the late 19th century indicate a consistent rise in both annual and winter temperatures in this region. The observed rises in average annual and seasonal temperatures are probably due to a weakening of the southwestern edge of the Siberian high during winter, coupled with stronger summer thermal depressions over Central Asia.

While Central Asia has generally witnessed a decline in precipitation over the last 50 years, contrasting trends have been observed around the main oases of Kazakhstan, Uzbekistan, and Turkmenistan, including areas, such as Urganch, Bokhara, Toshkent, Murgab, Tedjen, and Ashgabat. This anomaly is probably related to local climate changes induced by humans, particularly due to irrigated lands' expansion (Pielke Sr. *et al.*, 2007).

Notwithstanding that numerous studies have addressed climate change and its potential impact on changes in vegetation cover in Uzbekistan (Chen *et al*., 2020; Godde *et al*., 2020; Lioubimtseva & Henebry, 2009; Seim *et al*., 2016; Zong *et al*., 2020), each one lacked a comprehensive approach and focused on a sizeable area, either Uzbekistan or the whole of Central Asia. Consequently, this has generally reduced the accuracy for specific ecosystems given that climatic variables can significantly vary even within one country. Likewise, many of the studies limited climatic factors to precipitation and temperature only, neglecting soil temperature and just using the NDVI index, whereas including other indices, such as the Soil Adjusted Vegetation Index (SAVI), can also provide valuable insights.

The principal goal of this research was to analyze vegetation cover change in Ugam Chatkal National Park from 1991 to 2022, considering its relationship with precipitation, temperature, and soil temperature. Based on this analysis, the aim was to predict the future climate and vegetation within the study area.

2. Research Methods

2.1. Study area

Ugam Chatkal National Park (UCHNP) is located in the northern part of the Tashkent province, Uzbekistan, covering approximately 668,350 hectares in the Boʻstonliq and Ohangaron districts of the Tashkent Region (Figure 1). This study focuses specifically on the Boʻstonliq District, encompassing an area of 4,930 km², used for remote sensing analysis.

The climate in the region is characterised as temperate continental, featuring hot summers and relatively cold winters. The annual average temperature is +15 °C, with an average January temperature of -9 °C and an average July temperature of +21 °C. Extreme temperatures range from a minimum of -26 °C to a maximum of +46 °C. The district receives an annual rainfall of 500–600 mm, with the majority occurring in spring and autumn. The growing season spans 210–215 days (Alikhanov *et al.*, 2021).

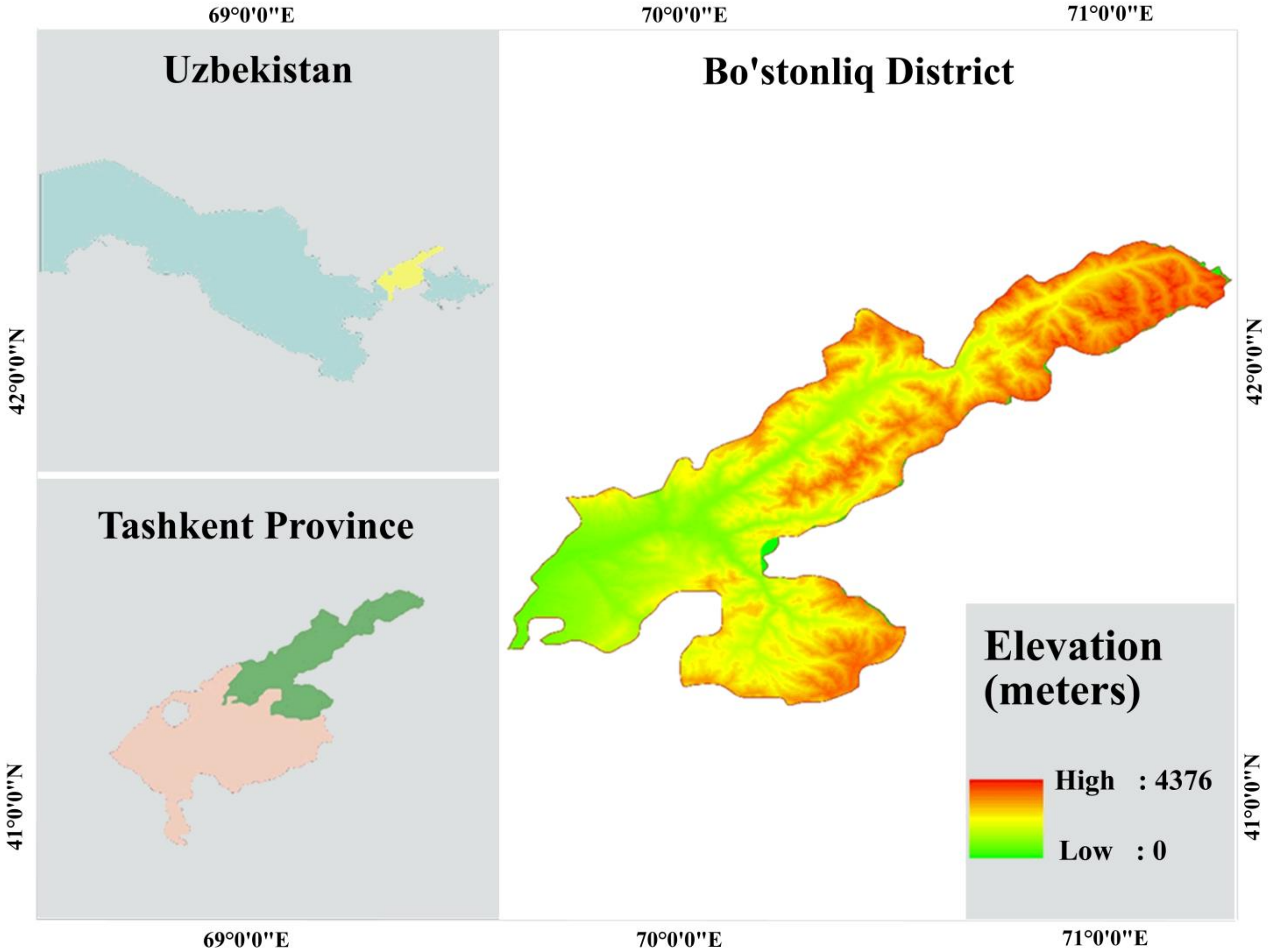

Figure 1. Study area: Ugam Chatkal National Park.

The topography of Boʻstonliq District is diverse, primarily consisting of hills and mountains. The northern area comprises high mountains, while lowlands are prevalent in the western and southern parts. Mountain ranges cover much of the area, including the eastern Tien Shan, the Pskem Mountains, and the Karzhantau, Ugam, and Chatkal ridges. Elevations increase from west to east and from south to north. The southern and western regions generally sit at altitudes of 1000 metres above sea level, while the remainder, dominated by highlands, ranges from 1200 to 4000 metres above sea level. The highest point in the vicinity is the peak of the Adelung Pskem ridge, reaching

4301 metres above sea level. Another notable summit, Beshtor, stands at 4299 metres. Numerous mountains and peaks, ranging from 1000 to 4000 metres above sea level, are scattered throughout the area, with several accessible by car (Alikhanov *et al*., 2021).

Bo'stonliq District has a significant role in supplying water and food to the entire Tashkent province, particularly Tashkent (the capital), which is dependent on the supply of water and meat from Bo'stonliq District. The official population of the capital is more than two million people, with unofficial numbers reaching four million (by means of permanent migrants from other regions). The government plans to expand the city with 200 km^2 of new land to the east. According to experts, this might increase the city's population to 5-7 million people, placing significant pressure on water and food supplies. Therefore, the environmental sustainability and resilience of the study area will be even more crucial in the near future.

2.2. Google Earth Engine

According to Mutanga & Kumar (2019), the Google Earth Engine (GEE) is a cloud platform for storing and processing geographical datasets in order to assess and generate final results. The cloud engine is linked to Google Earth, which has spatial datasets from various sensors saved within.

GEE analyses and processes substantial numbers of spatial data quickly and easily. Developers created it to facilitate the work of GIS specialists who occasionally deal with significant areas often over lengthy periods. Another advantage associated with GEE is that it does not demand that computers have the considerable computational capacity to analyse large data because the backend Google computers manage this specific task effectively.

The SAVI and the NDVI indices were adopted to analyse vegetation cover over the Ugam Chatkal National Park. If most of the research employed only the NDVI, testing and comparing other accurate indices with the NDVI results is imperative because they might deliver different results for a study area. Although the NDVI is the most commonly applied and tested vegetation index, it has a few shortcomings, as mentioned in the Introduction. The SAVI index, in contrast, is more resilient to atmospheric conditions and canopy cover (Soudani *et al.*, 2006).

On behalf of remote sensing analysis, three Landsat satellites were chosen: Landsat 5 TM (from 1991 to 2000), Landsat 7 ETM+ (2001 to 2014) and Landsat 8 OLI (from 2015 to 2022). Concerning the filter parameters, we chose 10% cloud cover for the study area. Consequently, not all images from the image collection list were included in the analysis, particularly if they were not of sufficient quality. Altogether more than 600 Landsat images covering four quadrats (153/31,153/32,154/31, 154/32) were processed using GEE for vegetation cover analysis. Generally, 115 Landsat 5 TM, 130 Landsat 7 TM and 86 Landsat 8 OLI surface reflectance satellite images were processed during the analysis of vegetation cover.

The most common way to detect the vegetation cover change of an ecosystem with remote sensing is by using vegetation indices for a satellite image. The most frequent index that researchers apply is the Normalised Difference Vegetation Index (NDVI) (Eisfelder *et al.*, 2023). The principle of the NDVI is simple – it calculates the ratio between the difference of near-infrared and red spectral bands and their sum, giving the final result that ranges from -1 (no vegetation) to +1 (maximum vegetation):

Most researchers have only tested the NDVI for the long-term spatial analysis of vegetation cover, given that it is the most established and highly recommended index, whilst they have neglected testing other vegetation indices. Despite its popularity, the NDVI has a variety of disadvantages. One is related to the impact of soil background, particularly soil brightness. In certain studies, applying the NDVI, darker soil substrates resulted in a higher vegetation index (Huete, 1988). Therefore, it was decided to develop a particular index that excludes the impact of soil on the final result. The Soil–Adjusted Vegetation Index developed by Huete (1988) includes factor L for the equation of NDVI that is supposed to adjust VI to the soil influence. L varies from 0 (in this case the SAVI [Equation 1] does not differ from the NDVI [Equation 2]) to 1 (high impact of soil and low vegetation cover).

$$\boldsymbol{SAVI = \frac{(NIR - RED)(1 + L)}{NIR + RED + L}} \tag{1}$$

The SAVI is repeatedly preferred in situations where accurate vegetation assessment is challenging due to the presence of bare soil or where soil variations are significant.

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{2}$$

2.3. Meteorological data

The meteorological data was collected from the Hydrometeorological Service Agency under the Ministry of Ecology, Environmental Protection and Climate Change of the Republic of Uzbekistan (Uzhydromet) for three decades (1991-2022). We deliberately collected data that might have a direct relationship with the vegetation cover and related to climate, specifically total monthly precipitation, average monthly temperature and average monthly soil temperature.

The temperature around a plant determines its rate of growth and development, and each species has a defined temperature range that is represented by minimum, maximum and optimal. In terms of plant output, extreme occurrences might be the most severely affected in the summer months. There is a higher chance that air temperatures may rise over the ideal range for many species in the event of increasing climate change. On account of the possibility of ordinary temperatures, the growth season for cool-season species will be limited (Hatfield & Prueger, 2015). Therefore, temperature values, both extreme and average, are important with respect to monitoring climate change and its effect on vegetation.

Numerous studies also investigated the impact of local precipitation on vegetation cover and biomass. Chang *et al*. (2011), for instance, analysed the relationships of temperature and precipitation on vegetation in forests in Taiwan and discovered that temperature has a greater impact on forest biomass than precipitation. In a different study completed in North American monsoon regions, authors determined a positive correlation between monthly precipitation and vegetation indices, derived from satellite data (Méndez-Barroso *et al*., 2009).

The measurement of the Earth's natural warmth is known as soil temperature. It regulates the ground's chemistry, life, and atmospheric-ground gas exchange. The phrase "soil surface temperature," which refers to the temperature difference between the top four inches (10 cm) of the ground and the surrounding air, may also arise. Variations in radiant energy and energy shifts at the surface of the ground may result from daily and seasonal changes in the temperature of the land. Soil temperature is a prominent factor influencing the processes governing soil properties and those involved in plant growth (Onwuka, 2018). Owing to the absence of soil moisture data for the study area concerning the study period, it was decided to analyse the data pertaining to average monthly soil temperature and its relationship with other parameters (Onwuka, 2018).

2.4. Statistical analysis

The impact of climatic factors on vegetation cover over the years can be analysed via statistical analysis, for example, Pearson's correlation analysis. Pearson's correlation coefficient often denoted as "R" is a statistical measure that quantifies the strength and direction of a linear relationship between two variables. The coefficient ranges from -1 to 1, where:

- 1: A perfect positive linear relationship
- 0: No linear relationship
- -1: A perfect negative linear relationship

The correlation coefficient's magnitude indicates the relationship's strength, while its sign indicates the direction (Schober *et al.*, 2018).

It is important to note that correlation does not imply causation. Even if two variables are strongly correlated, it does not necessarily imply that one causes the other to change. Other factors or coincidences may be involved. Therefore, more comprehensive regression analysis was conducted between the variables.

The coefficient of determination, often denoted as R2, is a statistical measure that represents the proportion of the variance in the dependent variable that is predictable from the independent variable(s). Essentially, it assesses the goodness of fit of a regression model. In the context of linear regression, the coefficient of determination is calculated as the square of the correlation coefficient (R) between the observed and predicted values of the dependent variable. Nonetheless, it is worth noting that R alone does not provide information regarding the appropriateness of the model or the validity of its assumptions.

Monthly time-series data was obtained to correlate climate with vegetation. We analysed mean monthly NDVI and SAVI indices for the study area and statistically analysed them together with the sum monthly precipitation, mean monthly soil moisture and mean monthly air temperature, measured in situ using local meteorological stations.

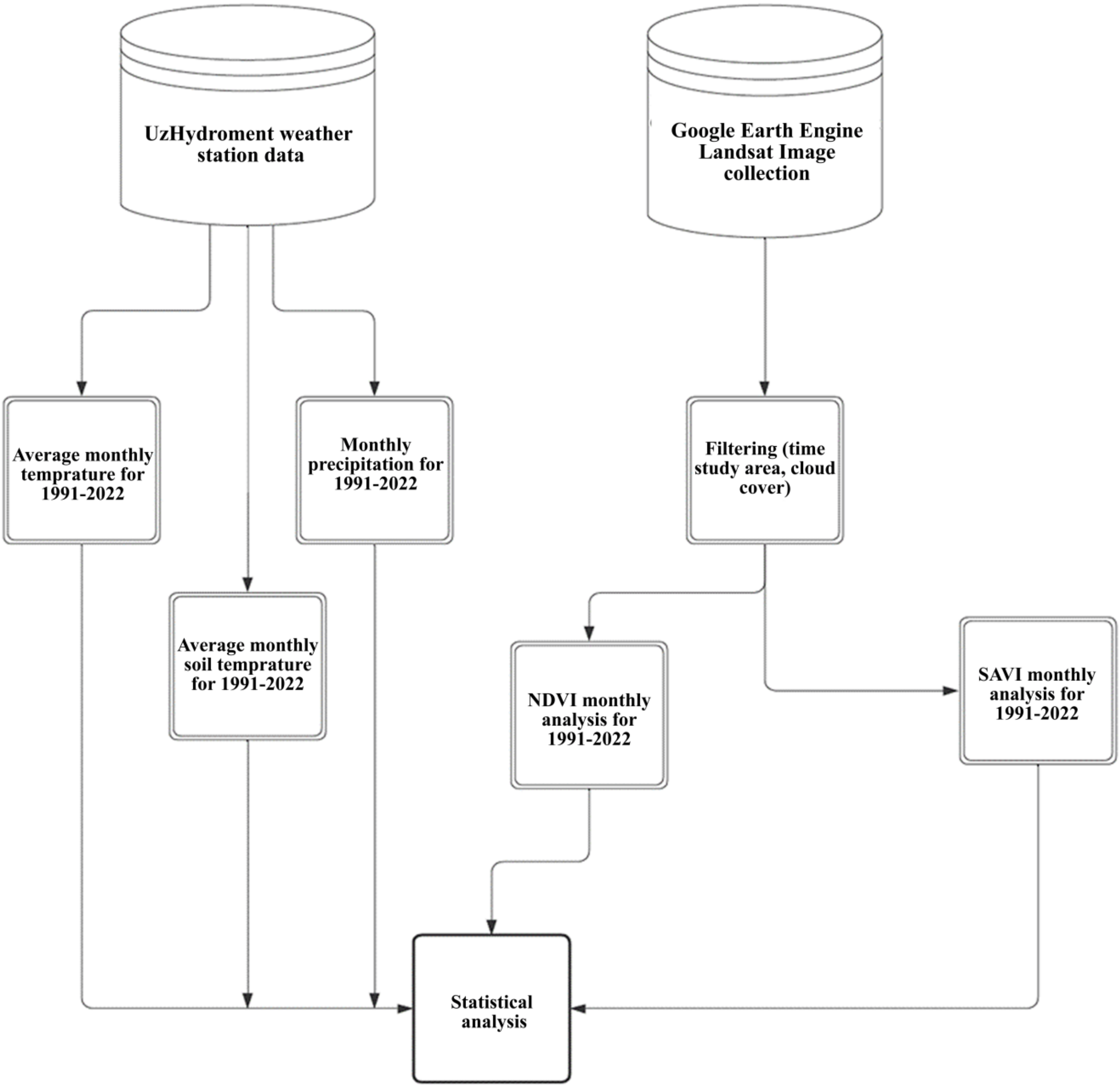

Figure 2. Flowchart of the analysis.

In statistical analysis, the p-value and F-statistic (or F-value) are valuable measures used to assess the significance of relationships and effects in regression analysis or analysis of variance (ANOVA). The p-value is a measure that determines the statistical significance of an observed effect or relationship. It represents the probability of obtaining results as extreme as the observed results (or more extreme) under the assumption that the null hypothesis is true. A small p-value (typically less than 0.05) implies that there is a significant statistical dependence between two variables.

The F-statistic is used in analysis of variance (ANOVA) and regression analysis to test the overall significance of the model. A large F-statistic and a small associated p-value suggest that the overall regression model is statistically significant and vice versa. The regression analysis among all the variables was performed using Microsoft Excel software 2020 with the assistance of the Analysis Toolpak to evaluate the data.

3. Results and Discussion

3.1. Vegetation Time-series Analysis

The results of the time-series vegetation analysis for the post-Soviet period exhibit that vegetation cover fluctuates during seasons and years, showing high values in one year and low values in other years (Figures 3, 4, and 5). In particular, the NDVI index presents higher values than the SAVI for the same date, whereas for low values (during winter time), both the SAVI and the NDVI display equal values. During peak vegetation periods (spring and early summer), the mean NDVI reaches values ranging from 0.4 to 0.55. Meanwhile, in winter periods, the lowest values for the NDVI drop to -0.2 - -0.1 for UCHNP.

Concerning the SAVI index, maximum values range from 0.25 to 0.3, sometimes falling to 0.25. For this study, the minimum values for the SAVI during winter periods area is similar to its sibling, the NDVI index. Overall, both indices exhibit the same trend, ascending and descending, with only a few years displaying slightly different results, such as the beginning of years 2004, 2014 and 2016.

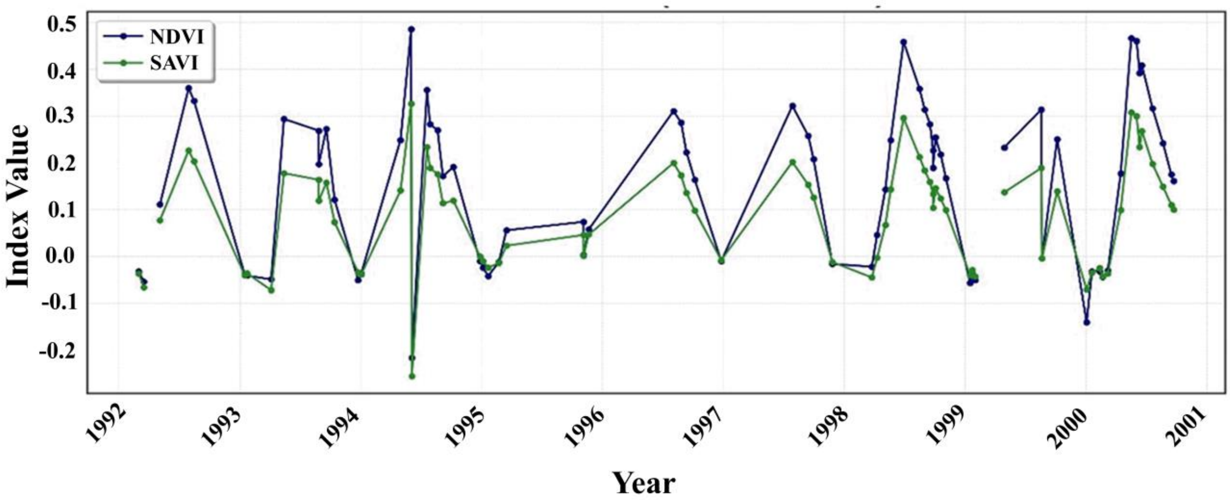

Figure 3. NDVI and SAVI average monthly values for the study area using Landsat 5 TM surface reflectance.

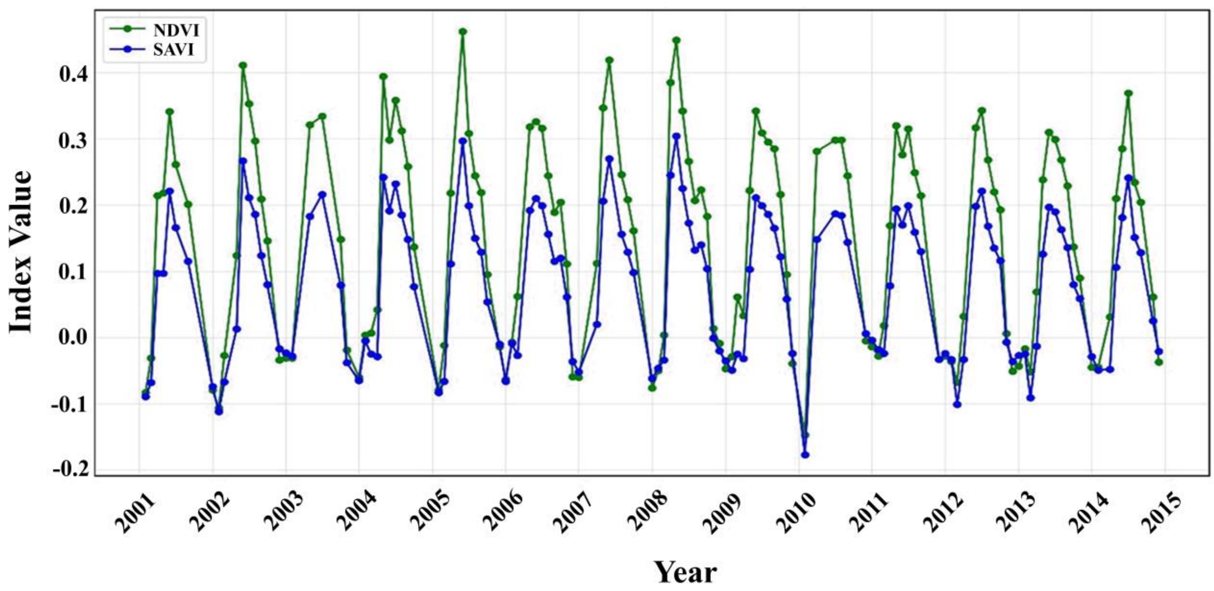

Figure 4. NDVI and SAVI average monthly values for the study area using Landsat 7 ETM surface reflectance.

Besides monthly mean, minimum, maximum, 25 percentile (p25), median and 75 percentile (p75), the NDVI and SAVI values were also calculated for each month. Subsequently, they were summarised into average annual minimum, maximum, median, mean and p75 values (Figures 6 and 7).

It is evident from the figures that the mean annual statistical values for both indices fluctuate from 1991 to 1999. It then stabilises from the beginning of the century and fluctuates again. Of note is that, starting in 2015, minimum and maximum values began to increase, attaining their maximum and minimum possible values virtually for both the NDVI and SAVI. This might indicate a potential trend towards more extreme seasonal climates, ranging from cold winters to very hot summers, with noticeable seasonal precipitation variations. Mean, median, p25 and p75 values also experienced a slight increase during the last 30 years of the post-Soviet period (Figures 6 and 7).

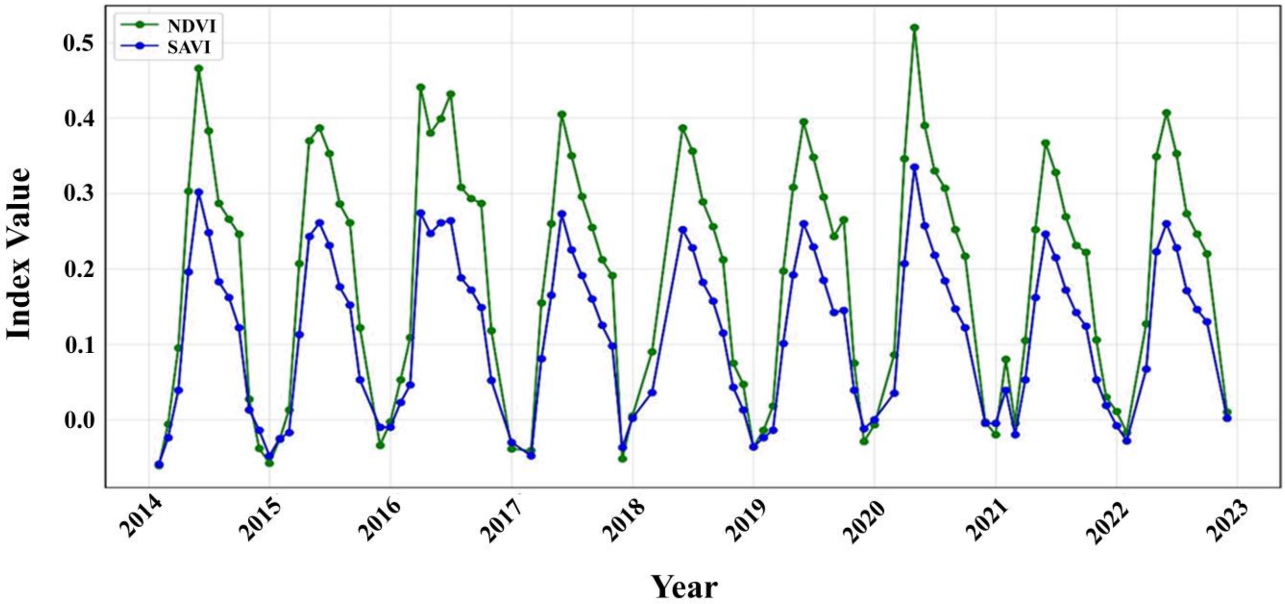

Figure 5. NDVI and SAVI average monthly values for the study area using Landsat 8 OLI surface reflectance

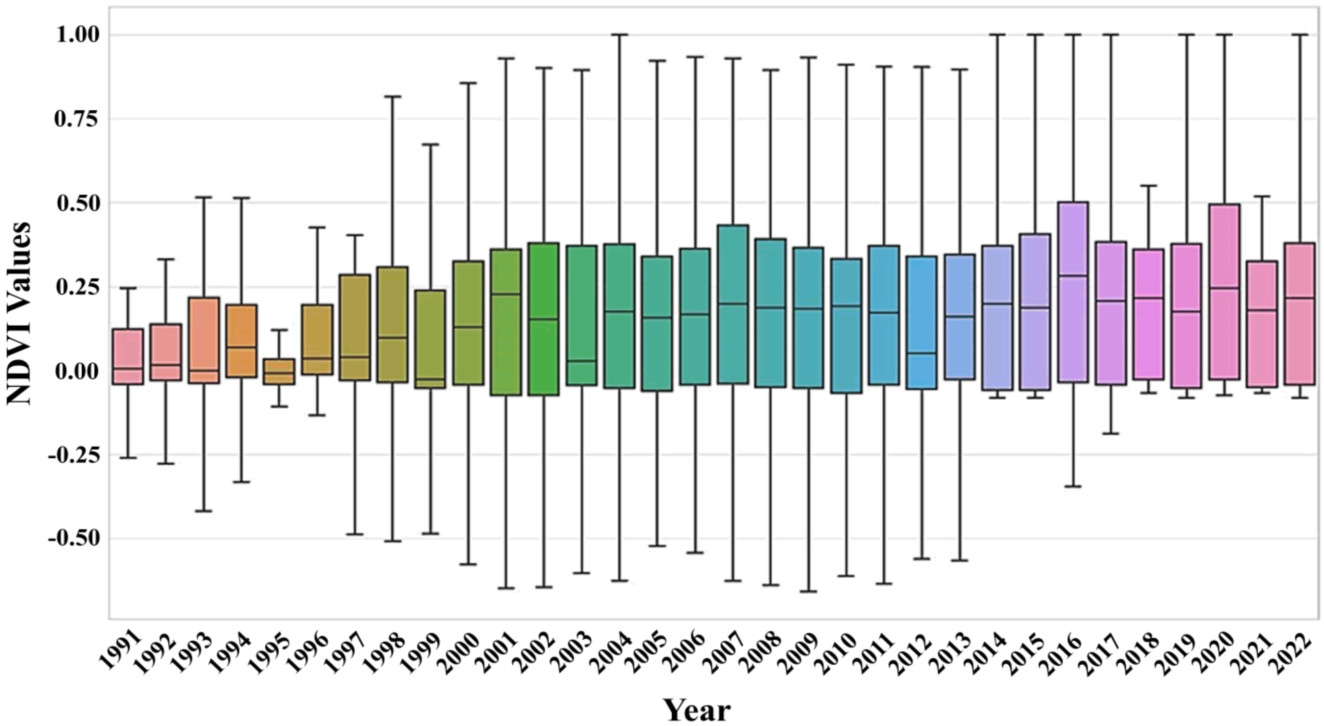

Figure 6. Annual NDVI minimum, 25% percentile, median, 75% percentile and maximum values.

3.2. Climate time-series analysis

Throughout the study period, climatic parameters, specifically soil temperature, air temperature and precipitation were also analysed. Mean monthly air temperature was obtained from Uzhydromet for time-series correlation analysis with the NDVI and the SAVI indices. It should be mentioned that the mean monthly air temperature and soil temperature are calculated using the mean daily temperatures, which are measured for each hour.

As Figure 8 shows, mean annual temperature reveals an increasing trend during the course of the last thirty years for the study period, with a strong moderate correlation R=0.58 (and R2 = 0.33). Mean annual soil temperature also demonstrates an increasing trend all through the study period, but with a significantly less correlation R= 0.17 (R2= 0.03) (Figure 9). Sum annual precipitation from 1991 to 2022 also exhibits a gradual increasing trend for the UCHNP. Nevertheless, the relationship is also weak, with a weak positive correlation R =0.18 (R2 = 0.033).

Mean annual air temperature shows slight fluctuations throughout the study period, but generally presents a gradual increasing trend. Soil temperature inter-annual results also do not significantly differ from each other, except for certain years, such as 1994, 2006, 2012 and 2017, when annual mean soil temperature displayed either high or low results compared to other years (Figure 9).

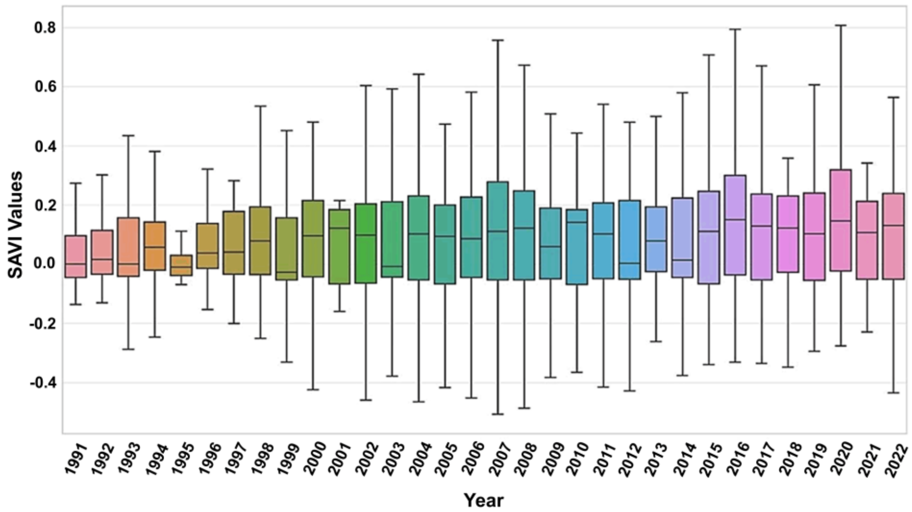

Figure 7. Annual SAVI minimum, 25% percentile, median, 75% percentile and maximum values

However, annual precipitation for the region illustrates dramatic fluctuations, especially at the beginning of the period. For example, in 1993 annual precipitation reached 1400 mm, then dropped to 430 mm for the year 1995. In 1997, the region again experienced a high level of annual precipitation (1300 mm), which then dropped to 700 mm in 2000. The remaining years also reveals similar patterns, although to a lesser extent (Figure 10).

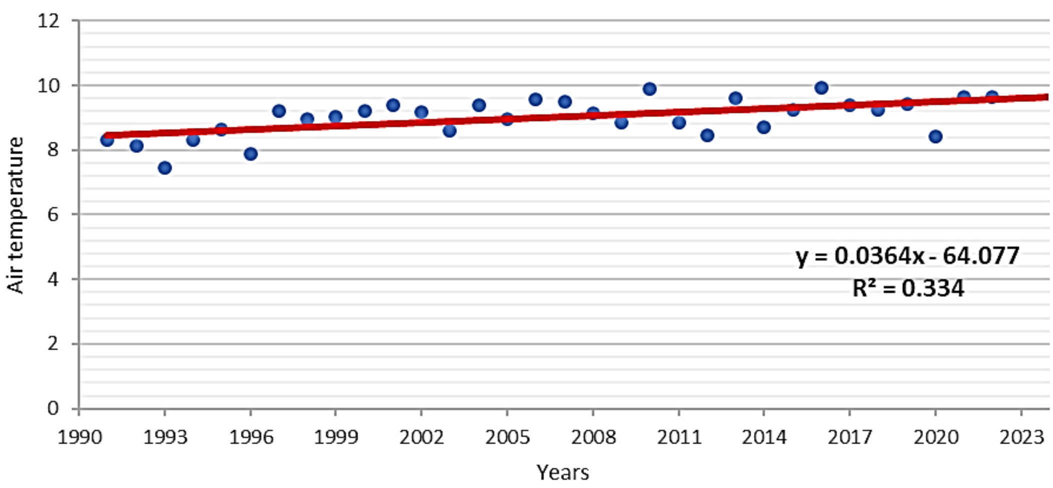

Figure 8. Mean annual precipitation trend from 1991 to 2022

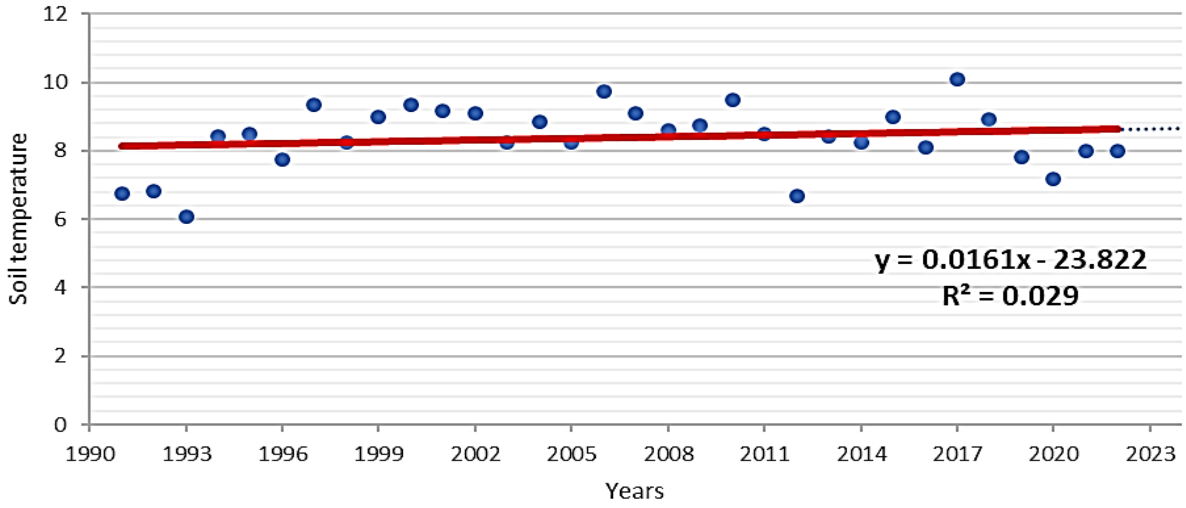

Figure 9. Mean annual soil temperature trend from 1991 to 2022.

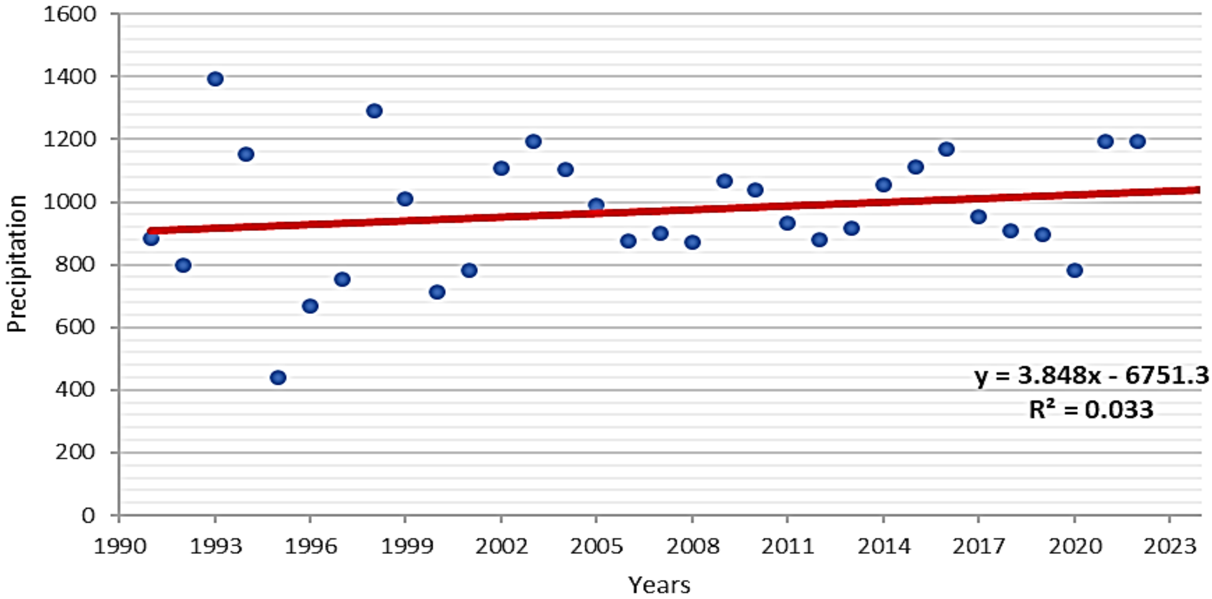

Figure 10. Annual sum precipitation trend from 1991 to 2022.

3.3. Correlation analysis between vegetation and climate

Correlation and the coefficient of determination matrices below (Figures 11 and 12) illustrate that the highest interdependency among all variables show Air Temperature vs. Soil Temperature, NDVI vs. SAVI, reaching almost the maximum value (R =0.98). The relationship between air temperature and soil temperature on a larger scale is complex and depends on various factors, such as the type of soil, moisture content and local environmental conditions. However, in this study area, both parameters were measured at the same location, the Chimgan weather station. In colder seasons, a drop in air temperature can lead to a decrease in soil temperature. The soil tends to lose heat to the atmosphere during colder periods. Conversely, during warmer seasons, higher air temperature can result in an increase in soil temperature as the soil absorbs heat from the air. We have a very strong linear dependency (R =0.98, R2 = 0.96) (Figures 11 and 12).

Another very strong linear correlation displays both the NDVI and the SAVI indices, which is not surprising, for the reason that these indices have similar formulas and employ the same technique to detect vegetation (R =0.98, R2= 0.96). The only difference between the NDVI and the SAVI is the L factor, which is used to minimise the soil background factor on the reflectance.

The NDVI and the SAVI also have a high positive correlation with air temperature and soil temperature. The SAVI has slightly stronger relationship with both air temperature and soil temperature (Rair=0.86 and Rsoil = 0.86), as opposed to the NDVI (Rair=0.83 and Rsoil = 0.84). These values are considered as strong and positive, meaning that both air temperature and soil directly impact the growth and health of vegetation. The determination coefficients are also high: R2air=0.69 and R2soil = 0.71 for the NDVI and R2air=0.69 and R2soil = 0.71 for the SAVI (Figure 11 and 12).

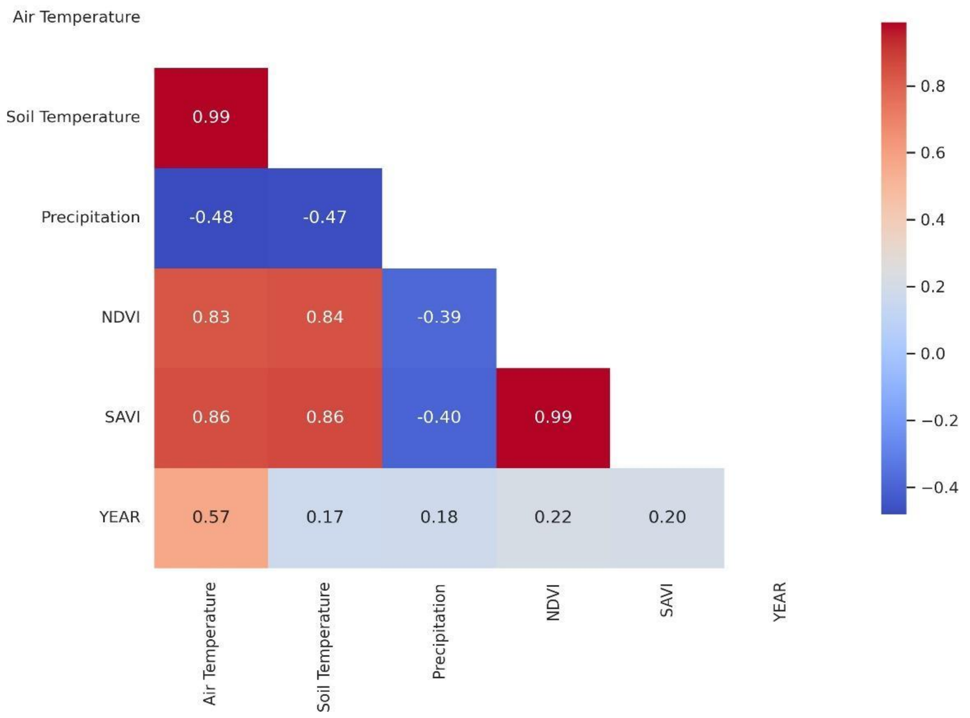

Figure 11. Correlation matrix (R).

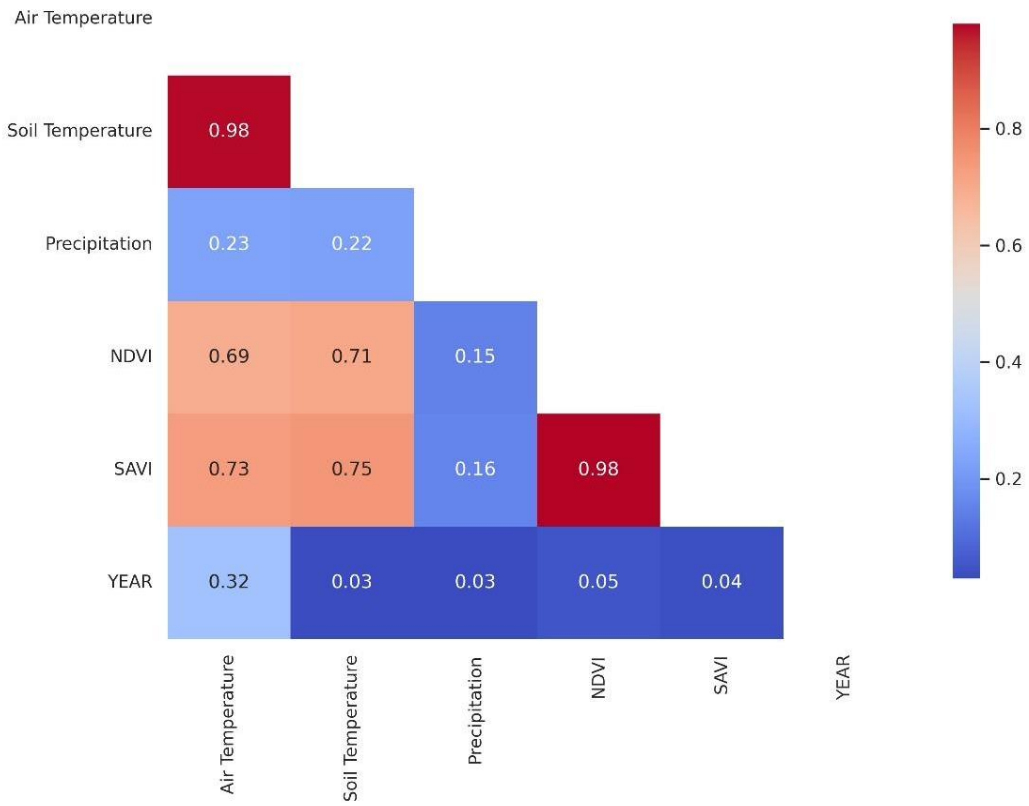

Figure 12. Coefficient of determination matrix(R^2).

Also strong moderate relationship has air temperature with year (which denotes that in the future, temperatures in the region will continue to rise) with R = 0.57 (R2 =0.33). Similarly, moderate negative relationships exist between air and soil temperature on precipitation (Rair=-0.48 and Rsoil= -0.47). However, precipitation (as an independent variable) has a weak moderate negative impact on the SAVI and the NDVI (-0.4 and -0.39). Besides precipitation, vegetation in the study area can take water from groundwater resources and melting glaciers in the mountains.

The NDVI and the SAVI also have a high positive correlation with air temperature and soil temperature. The SAVI has a slightly stronger relationship with both air temperature and soil temperature (Rair=0.86 and Rsoil = 0.86), as opposed to the NDVI (Rair=0.83 and Rsoil = 0.84). These values are considered strong and positive, signifying that both air temperature and soil directly impact vegetation growth and health. The determination coefficients are also high: R2air=0.69 and R2soil = 0.71 for the NDVI R2air=0.69 and R2soil = 0.71 for the SAVI (Tables 1 and 2).

Table 1. p-value of relationship among variables.

	NDVI	Air Temperature	Soil Temperature	Precipitation
NDVI	-	1.30E-78	5.96E-82	3.38E-12
SAVI	1.45E-285	1.169E-87	3.029E-91	9.13E-13
Air Temperature		-	1.19E-141	1.54E-23
Soil Temperature			-	7.19E-23

According to Table 3, the SAVI, NDVI, precipitation and soil temperature tend to increase with time, although the relationship is weak. This can be said with some degree of certainty. It is worth mentioning that the p-values for all relationships were calculated to be less than 0.05, which means that there is statistical evidence to reject the null hypothesis, indicating that at least one predictor variable is significantly related to the response variable. In spite of this, the p-value alone does not measure the strength of the relationship (Table 2).

A high F-statistic in the context of regression analysis specifies that the model (with predictors) fits the data significantly better than a model without predictors. This is frequently associated with the overall significance of the regression model. In our models, the high F-statistic indicates that the model as a whole provides a better fit than a model with no predictors.

Table 2. F-statistics of relationship among variables.

	NDVI	Air Temperature	Soil Temperature	Precipitation
NDVI	-	674.24	725.56	52.68
SAVI	23520.98	821.78	885.53	55.75
Air Temperature		-	15105.60	114.44
Soil Temperature			-	110.49

It is vital to consider the practical significance of the results. A statistically significant relationship does not necessarily signify a practically meaningful one. Additionally, other factors, such as effect size, domain knowledge, and the context of the study should be considered when interpreting the results.

In brief, the interpretation should be cautious, acknowledging that while there may be a statistically significant relationship, the practical significance or strength of the relationship may be limited based on the low correlation and R-squared.

3.4. Forecast

Forecast was undertaken using the Forecast Microsoft Excel function based on monthly data derived from Google Earth Engine (for the vegetation) and the Chimgan meteorological station (for the climate data). It was subsequently summed up as average annual to enable the data to be presented conveniently.

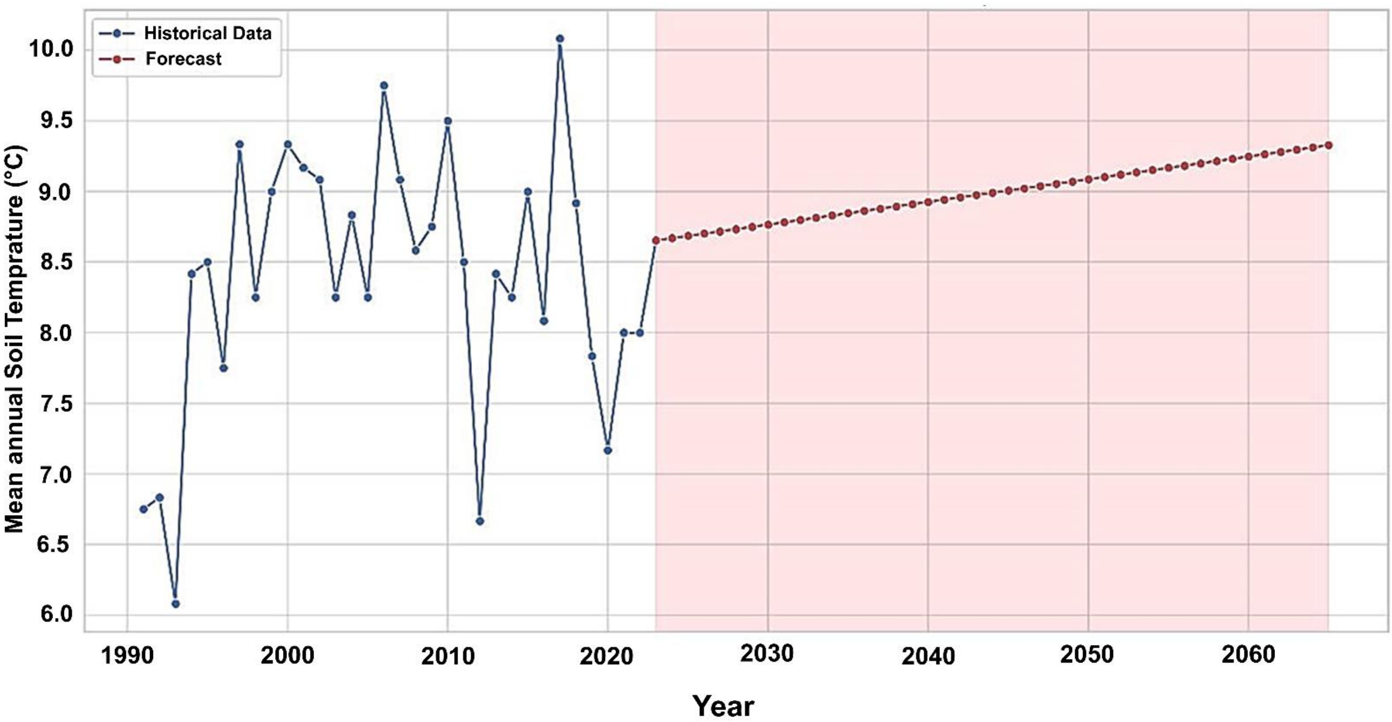

Figure 13. Mean annual soil temperature forecast until 2065.

According to the data obtained from the Uzhydromet for the last thirty years, annual precipitation will increase. In 2040, the annual precipitation will reach 1100 mm, gradually rising to 1150 mm in 2050 and 1200 mm in 2065.

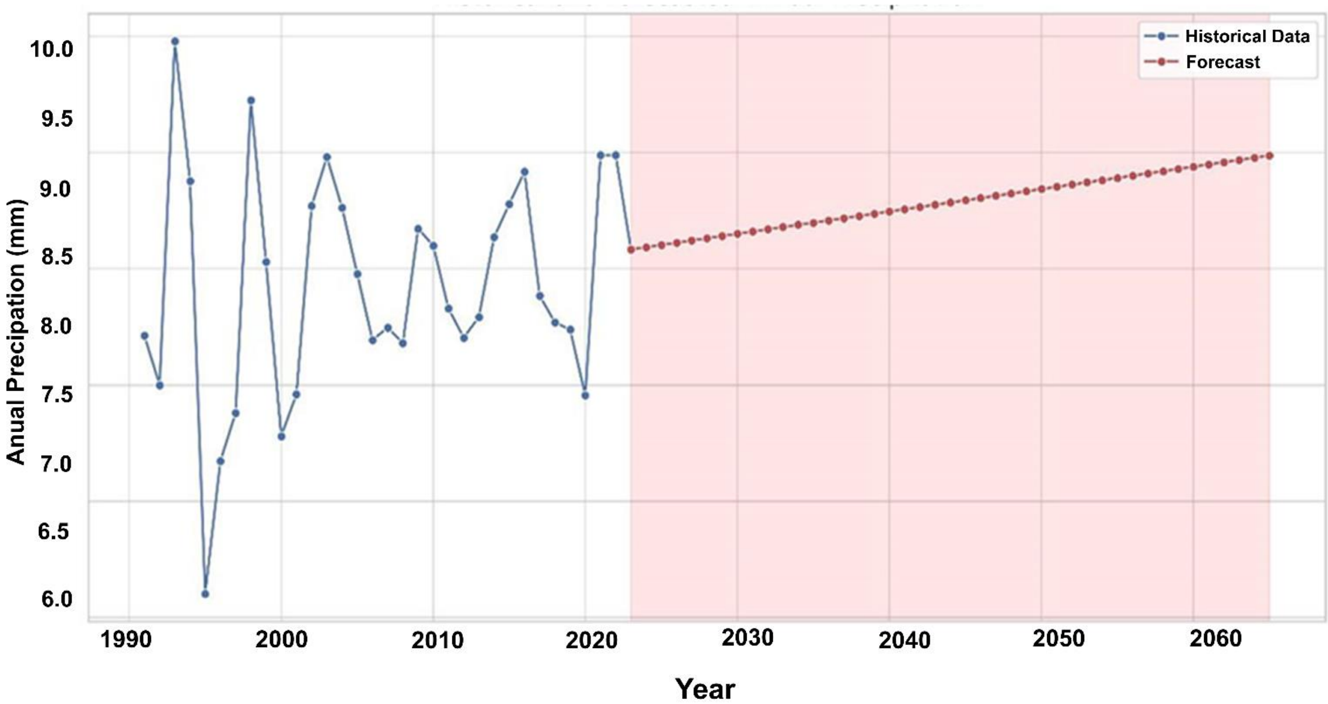

Figure 14. Mean annual precipitation forecast until 2065.

As can be determined from Figures 13, 14, and 15, each of the climatic parameters will increase within the next four decades (until 2065). However, it should be noted that only air temperature demonstrated a sufficient correlation with year to consider the trend as reliable. The other two indicators have too weak a correlation to predict with certainty that they will also increase, in particular precipitation, which does not depend on air temperature. Similarly, as the green line shows, all parameters fluctuate significantly from year to year. Therefore, the red forecast line is just an assumption of the general trend for upcoming decades.

Mean annual soil temperature is expected to reach 8.7 C° in 2030, gradually continuing to rise to 9 C° in 2040, reaching 9.3 C° in 2060 (Figure 13). In sum, within 40 years, mean annual soil temperature will increase by 0.6 C°. Soil temperature affects microbial activity and nutrient cycling. Changes in soil temperature can influence decomposition rates and the availability of nutrients, impacting ecosystem processes. Moreover, temperature changes can influence water availability in soil. Warmer temperatures may increase evaporation rates, potentially causing drier soil conditions.

Likewise, warmer soil temperatures can accelerate plant growth and extend growing seasons in certain cases. Conversely, negative impacts can offset these benefits, such as increased evaporation rates, which can lead to soil moisture stress. This moisture stress can reduce plant productivity, alter species composition and potentially decrease biodiversity. In some instances, increased temperatures can also exacerbate the spread of invasive species, which can further disrupt the native vegetation.

Air temperature has the highest correlation with time among all climatic parameters; as a result, its forecast for the future should be seriously considered. According to the trend, during the next 40 years, the average annual air temperature will increase to 11.2 C° (for 1.6 C°) (Figure 15). Altered temperature patterns may result in changes in the distribution of plant species. Several species may be more resilient to higher temperatures, while others may struggle to adapt. Altered temperatures may affect the habitat and migration patterns of wildlife species, with particular species needing to adapt or migrate to more suitable environments. Moreover, higher temperatures may contribute to increased drought risk in certain regions. Prolonged drought conditions can have severe consequences for both vegetation and animal populations.

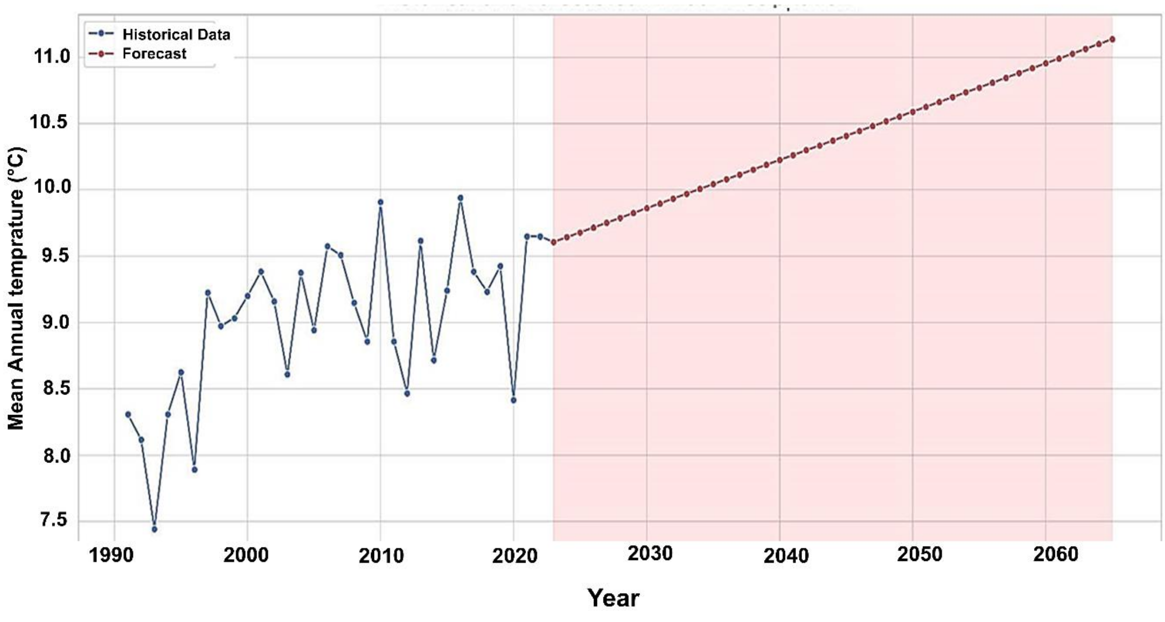

Figure 15. Mean annual air temperature forecast until 2065.

The vegetation cover is expected to increase due to the projected increase in air temperature and precipitation (Figures 16 and 17). In specific cases, increased precipitation and temperature can enhance vegetation growth. Warmer temperatures may extend the growing season, whilst higher precipitation levels can provide more water for plants. This could potentially produce increased vegetation cover and biomass. Certain species may become more prevalent, while others may decline, impacting overall vegetation structure.

Changes in vegetation cover and biomass can affect wildlife habitat and grazing resources. Increased biomass may provide more food for herbivores, although this also depends on the specific response of plant species and the potential for overgrazing. Different plant species have varying tolerances to changes in temperature and precipitation. As a result, some species may benefit from warmer conditions, while others may be negatively affected. The overall response will depend on the composition of the existing vegetation.

While increased precipitation can be beneficial for vegetation, it is essential to consider how water availability interacts with other factors. If temperatures rise substantially, increased evaporation may counterbalance the positive effects of higher precipitation.

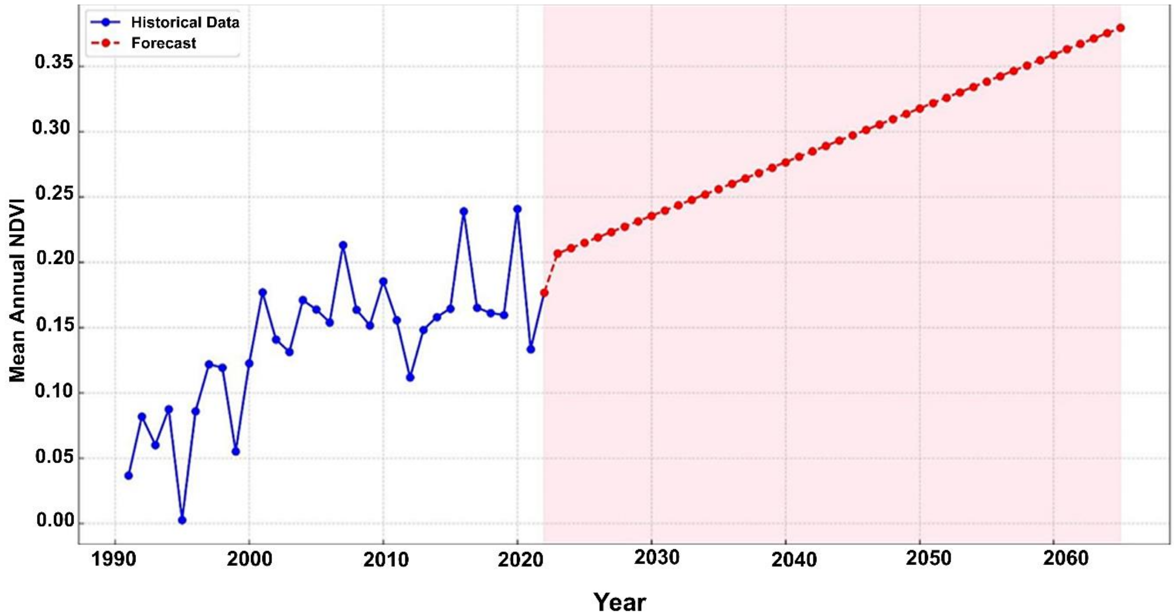

Figure 16. Mean annual NDVI forecast until 2065.

Changes in vegetation cover and biomass can have consequences for wildlife habitat and grazing resources. Increased biomass may provide more food for herbivores; nevertheless, this is also dependent on the specific response of plant species and the potential for overgrazing. While particular regions may experience a boost in vegetation cover, others might experience changes in the types of dominant plant species. Certain species may become more prevalent, while others may decline, impacting overall vegetation structure.

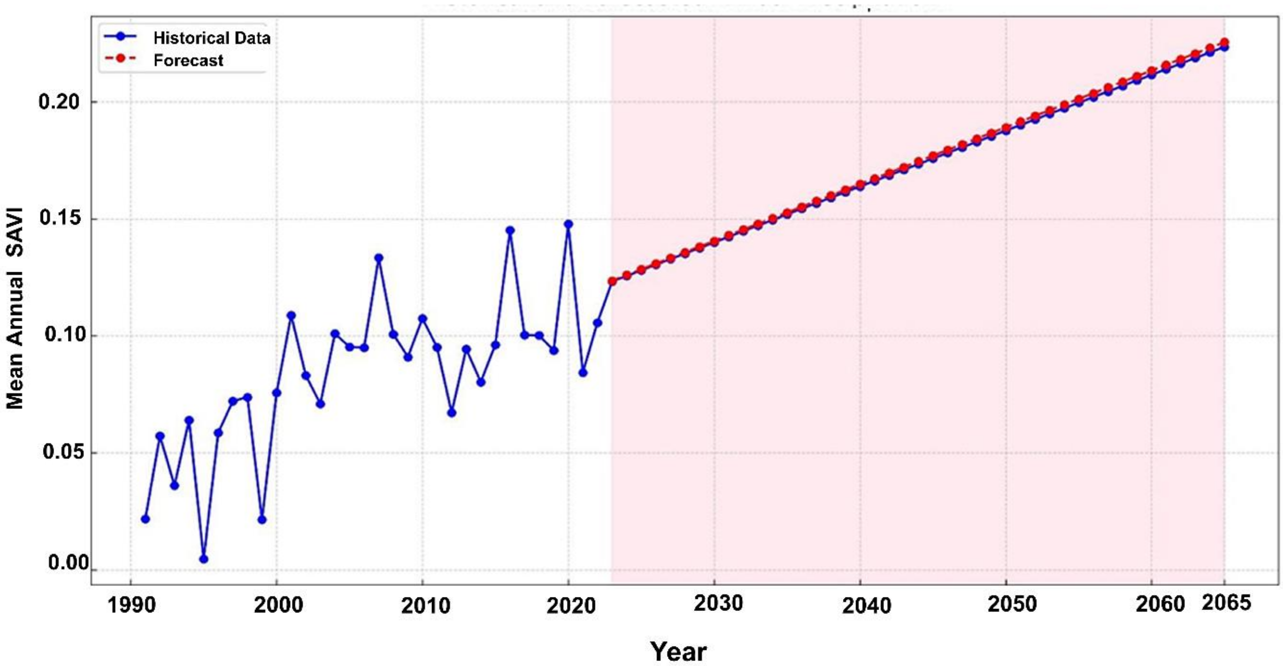

Figure 17. Mean annual SAVI forecast until 2065.

If the NDVI increases from the annual average of 0.21 (in 2022) to 0.35 (in 2060), the SAVI index reveals that the region will encounter less dramatic biomass growth - will increase from 0.13 (in 2022) to 0.22 (in 2060).

4. Conclusion

Comprehensive monthly and annual time-series analysis for the Ugam Chatkal National park for the post-Soviet period was conducted in this research, using remote sensing images (Landsat satellite) and climate data, taken from the Uzhydromet (Chimgan meteorological station). We analysed the impact of climate during the last thirty years as regards vegetation cover in the study region and both climatic and vegetation trends for the past, so as to predict future possible development.

To recap, the results of our research are: (1) all climatic parameters, namely soil temperature, air temperature and precipitation, significantly fluctuated from 1991 to 2022, with an increasing trend, in general; (2) vegetation cover, measured using the NDVI and SAVI indices also fluctuated, especially at the beginning of the study period, including a minimal increase in trend over time; (3) commencing from 2014, vegetation minimum and maximum values start to differ more; (4) only air temperature has a sufficient correlation with time (R = 0.57) to seriously consider local temperature rise during the post-Soviet period and the continuation of this process in the future; (5) among the climatic parameters, only air and soil temperatures exhibit a very strong relationship with each other (R = 0.98), whereas precipitation reveals a less significant relationship (Rair =-0.48 and Rsoil= -0.47); (6) both indices have a strong dependence relative to air (Rsavi= 0.86, Rndvi =0.83) and soil temperature (Rsavi= 0.85, Rndvi =0.84), and a negative relationship with precipitation (Rsavi= -0.40, Rndvi =-0.39); (7) the SAVI demonstrated a better statistical relationship with climatic parameters in comparison to the NDVI, but the difference is small; (8) annual air temperature is predicted to increase for 1.6 C° across the following four decades; (9) precipitation and soil temperature are also projected to increase. However, the reliability of this finding is small enough compared to air temperature. Hence, further studies are necessary to verify these findings; (10) vegetation biomass will also increase, although other altercations in vegetation biomass is complicated.

The study emphasises the significance of monitoring these environmental management and policy-making trends. It highlights the complex relationship between climate change and vegetation dynamics, which is essential to preserve ecological integrity. Besides constant monitoring of climate dynamics in the region, it is also beneficial to analyse the anthropogenic impact, such as overgrazing and urbanisation, in relation to the local vegetation.

Acknowledgements

The author gratefully aknowldge the anonymous reviewers who gave valuable comments.

Author Contributions

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

Conflict of interest

All authors declare that they have no conflicts of interest.

Data availability

Data is available upon Request..

Funding

This research received no external funding.

References

Adepoju, K., Adelabu, S., & Fashae, O. (2019). Vegetation Response to Recent Trends in Climate and Landuse Dynamics in a Typ-ical Humid and Dry Tropical Region under Global Change. *Advances in Meteorology*, 2019, 1–15. doi: 10.1155/2019/4946127.

Alikhanov, B., Juliev, M., Alikhanova, S., & Mondal, I. (2021). Assessment of influencing factor method for delineation of groundwater potential zones with geospatial techniques. Case study of Bostanlik district, Uzbekistan. Groundwater for Sustainable Development, 12, 100548. doi : 10.1016/j.gsd.2021.100548.

Chang, C. T., Lin, T. C., Wang, S. F., & Vadeboncoeur, M. A. (2011). Assessing growing season beginning and end dates and their relation to climate in Taiwan using satellite data. International Journal of Remote Sensing, 32(18), 5035–5058. doi: 10.1080/01431161.2010.494635.

Chen, T., Tang, G., Yuan, Y., Guo, H., Xu, Z., Jiang, G., & Chen, X. (2020). Unraveling the relative impacts of climate change and human activities on grassland productivity in Central Asia over last three decades. *Science of The Total Environment*, 743, 140649. doi: 10.1016/j.scitotenv.2020.140649.

Dech, S., Holzwarth, S., Asam, S., Andresen, T., Bachmann, M., Boettcher, M., Dietz, A., Eisfelder, C., Frey, C., Gesell, G., Gessner, U., Hirner, A., Hofmann, M., Kirches, G., Klein, D., Klein, I., Kraus, T., Krause, D., Plank, S., & Kuenzer, C. (2021). Poten-tial and Challenges of Harmonizing 40 Years of AVHRR Data: The TIMELINE Experience. *Remote Sensing*, 13(18), 3618. doi: 10.3390/rs13183618.

Dong, J., Li, L., Li, Y., & Yu, Q. (2022). Inter-comparisons of mean, trend and interannual variability of global terrestrial gross pri-mary production retrieved from remote sensing approach. *Science of The Total Environment*, 822, 153343. doi: 10.1016/j.scitotenv.2022.153343.

Eisfelder, C., Asam, S., Hirner, A., Reiners, P., Holzwarth, S., Bachmann, M., Gessner, U., Dietz, A., Huth, J., Bachofer, F., & Kuen-zer, C. (2023). Seasonal Vegetation Trends for Europe over 30 Years from a Novel Normalised Difference Vegetation In-dex (NDVI) Time-Series—The TIMELINE NDVI Product. *Remote Sensing*, 15(14), 3616. doi: 10.3390/rs15143616.

Faour, G., Mhawej, M., & Nasrallah, A. (2018). Global trends analysis of the main vegetation types throughout the past four dec-ades. *Applied Geography*, 97, 184–195. doi: 10.1016/j.apgeog.2018.05.020.

Feng, X., Li, J., Cheng, W., Fu, B., Wang, Y., Lü, Y., & Shao, M. (2017). Evaluation of AMSR-E retrieval by detecting soil moisture decrease following massive dryland re-vegetation in the Loess Plateau, China. *Remote Sensing of Environment*, 196, 253–264. doi: 10.1016/j.rse.2017.05.012.

Fu, Y. H., Piao, S., Opde, Beeck, M., Cong, N., Zhao, H., Zhang, Y., Menzel, A., & Janssens, I. A. (2014). Recent spring phenology shifts in western C entral E urope based on multiscale observations. *Global Ecology and Biogeography*, 23(11), 1255–1263. doi: 10.1111/geb.12210.

Gabban, A., Liberta, G., San-Miguel-Ayanz, J., & Barbosa, P. (2004). Forest fire risk estimation from time series analisys of NOAA NDVI data. *Remote Sensing for Agriculture, Ecosystems, and Hydrology*, 5232, 587-595. doi: 10.1117/12.511003.

Godde, C. M., Boone, R. B., Ash, A. J., Waha, K., Sloat, L. L., Thornton, P. K., and Herrero, M. (2020). Global rangeland production systems and livelihoods at threat under climate change and variability. *Environmental Research Letters*, 15(4), 044021. doi : 10.1088/1748-9326/ab7395.

Hatfield, J. L., & Prueger, J. H. (2015). Temperature extremes: Effect on plant growth and development. *Weather and Climate Ex-tremes*, 10, 4–10. doi: 10.1016/j.wace.2015.08.001.

Helldén, U., & Tottrup, C. (2008). Regional desertification: A global synthesis. *Global and Planetary Change*, 64(3–4), 169–176. doi: 10.1016/j.gloplacha.2008.10.006..

Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment, 25(3), 295–309. doi: 10.1016/0034-4257(88)90106-X

Hussien, K., Kebede, A., Mekuriaw, A., Beza, S. A., & Erena, S. H. (2023). Spatiotemporal trends of NDVI and its response to cli-mate variability in the Abbay River Basin, Ethiopia. *Heliyon*, 9(3), e14113. doi : 10.1016/j.heliyon.2023.e14113.

Kalisa, W., Igbawua, T., Henchiri, M., Ali, S., Zhang, S., Bai, Y., & Zhang, J. (2019). Assessment of climate impact on vegetation dynamics over East Africa from 1982 to 2015. *Scientific Reports*, 9(1), 16865. doi : 10.1038/s41598-019-53150-0.

Lieberherr, G., & Wunderle, S. (2018). Lake Surface Water Temperature Derived from 35 Years of AVHRR Sensor Data for Euro-pean Lakes. *Remote Sensing*, 10(7), 990. doi: 10.3390/rs10070990.

Lioubimtseva, E., Cole, R., Adams, J. M., & Kapustin, G. (2005). Impacts of climate and land-cover changes in arid lands of Cen-tral Asia. *Journal of Arid Environments*, 62(2), 285–308. doi: 10.1016/j.jaridenv.2004.11.005.

Lioubimtseva, E., & Henebry, G. M. (2009). Climate and environmental change in arid Central Asia: Impacts, vulnerability, and adaptations. *Journal of Arid Environments*, 73(11), 963–977. doi: 10.1016/j.jaridenv.2009.04.022.

Méndez-Barroso, L. A., Vivoni, E. R., Watts, C. J., & Rodríguez, J. C. (2009). Seasonal and interannual relations between precipita-tion, surface soil moisture and vegetation dynamics in the North American monsoon region. *Journal of Hydrology*, 377(1–2), 59–70. doi: 10.1016/j.jhydrol.2009.08.009.

Michael, Y., Helman, D., Glickman, O., Gabay, D., Brenner, S., & Lensky, I. M. (2021). Forecasting fire risk with machine learning and dynamic information derived from satellite vegetation index time-series. *Science of The Total Environment*, 764, 142844. doi: 10.1016/j.scitotenv.2020.142844.

Momm, H. G., Elkadiri, R., & Porter, W. (2020). Crop-Type Classification for Long-Term Modeling: An Integrated Remote Sensing and Machine Learning Approach. *Remote Sensing*, 12(3), 449. doi: 10.3390/rs12030449.

Mutanga, O., & Kumar, L. (2019). Google Earth Engine Applications. *Remote Sensing*, 11(5), 591. doi : 10.3390/rs11050591.

Na, L., Na, R., Bao, Y., & Zhang, J. (2021). Time-Lagged Correlation between Soil Moisture and Intra-Annual Dynamics of Vegeta-tion on the Mongolian Plateau. *Remote Sensing*, 13(8), 1527. doi: 10.3390/rs13081527.

Onwuka, B. (2018). Effects of Soil Temperature on Some Soil Properties and Plant Growth. *Advances in Plants & Agriculture Re-search*, 8(1). doi: 10.15406/apar.2018.08.00288.

Paudel, K. P., & Andersen, P. (2010). Assessing rangeland degradation using multi temporal satellite images and grazing pressure surface model in Upper Mustang, Trans Himalaya, Nepal. *Remote Sensing of Environment*, 114(8), 1845–1855. doi: 10.1016/j.rse.2010.03.011.

Pielke Sr., Adegoke, R. A. J., Beltrán-Przekurat, A., Hiemstra, C. A., Lin, J., Nair, U. S., Niyogi, D., & Nobis, T. E. (2007). An over-view of regional land-use and land-cover impacts on rainfall. *Tellus B: Chemical and Physical Meteorology*, 59(3), 587. doi: 10.1111/j.1600-0889.2007.00251.x.

Pouliot, D., Latifovic, R., & Olthof, I. (2009). Trends in vegetation NDVI from 1 km AVHRR data over Canada for the period 1985–2006. *International Journal of Remote Sensing*, 30(1), 149–168. doi: 10.1080/01431160802302090.

Ranjana, R. Y. M., Weiqang, Ma, B. B., & Barjeece Bashir. (2020). Interannual Variation of NDVI, Precipitation and Tempera-ture during the Growing Season in Langtang National Park, Central Himalaya, Nepal. *Applied Ecology and Environmen-tal Sciences*, 8(5), 218–228. doi: 10.12691/aees-8-5-5.

Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation Coefficients: Appropriate Use and Interpretation. *Anesthesia & Analge-sia*, 126(5), 1763–1768. doi: 10.1213/ANE.0000000000002864.

Seim, A., Omurova, G., Azisov, E., Musuraliev, K., Aliev, K., Tulyaganov, T., Nikolyai, L., Botman, E., Helle, G., Dorado Liñan, I., Jivcov, S., & Linderholm, H. W. (2016). Climate Change Increases Drought Stress of Juniper Trees in the Mountains of Central Asia. *PLOS ONE*, 11(4), e0153888. doi: 10.1371/journal.pone.0153888.

Soudani, K., François, C., Le Maire, G., Le Dantec, V., & Dufrêne, E. (2006). Comparative analysis of IKONOS, SPOT, and ETM+ data for leaf area index estimation in temperate coniferous and deciduous forest stands. *Remote Sensing of Environment*, 102(1–2), 161–175. doi: 10.1016/j.rse.2006.02.004.

Sun, H., Wang, J., Xiong, J., Bian, J., Jin, H., Cheng, W., & Li, A. (2021). Vegetation Change and Its Response to Climate Change in Yunnan Province, China. *Advances in Meteorology*, 2021, 1–20. doi: 10.1155/2021/8857589.

Tian, F., Fensholt, R., Verbesselt, J., Grogan, K., Horion, S., & Wang, Y. (2015). Evaluating temporal consistency of long-term global NDVI datasets for trend analysis. *Remote Sensing of Environment*, 163, 326–340. doi: 10.1016/j.rse.2015.03.031.

Tottrup, C., & Rasmussen, M. S. (2004). Mapping long-term changes in savannah crop productivity in Senegal through trend anal-ysis of time series of remote sensing data. *Agriculture, Ecosystems & Environment*, 103(3), 545–560. doi: 10.1016/j.agee.2003.11.009.

Walker, J. J., & Soulard, C. E. (2019). Phenology Patterns Indicate Recovery Trajectories of Ponderosa Pine Forests After High-Severity Fires. *Remote Sensing*, 11(23), 2782. doi: 10.3390/rs11232782.

Wang, J., Rich, P. M., & Price, K. P. (2003). Temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA. *International Journal of Remote Sensing*, 24(11), 2345–2364. doi: 10.1080/01431160210154812.

Wang, J., Wang, K., Zhang, M., & Zhang, C. (2015). Impacts of climate change and human activities on vegetation cover in hilly southern China. *Ecological Engineering*, 81, 451–461. doi: 10.1016/j.ecoleng.2015.04.022.

Zhao, J., Huang, S., Huang, Q., Wang, H., Leng, G., Peng, J., & Dong, H. (2019). Copula-Based Abrupt Variations Detection in the Relationship of Seasonal Vegetation-Climate in the Jing River Basin, China. *Remote Sensing*, 11(13), 1628. doi: 10.3390/rs11131628.

Zhao, X., Yu, M., Pan, S., Jin, F., Zou, D., & Zhang, L. (2023). Spatio-temporal distribution and trends monitoring of land desertifi-cation based on time-series remote sensing data in northern China. *Environmental Earth Sciences*, 82(11), 263. doi: 10.1007/s12665-023-10950-y.

Zong, X., Tian, X., & Yin, Y. (2020). Impacts of Climate Change on Wildfires in Central Asia. *Forests*, 11(8), 802. doi: 10.3390/f11080802.