Analysis of desertification trends in Central Asia based on MODIS Data using Google Earth Engine

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Abstract. Desertification is a significant environmental issue affecting arid and semi-arid regions globally, including Central Asia. Monitoring and analyzing desertification trends is crucial for understanding the extent of land degradation and implementing effective management strategies. This literature review aims to provide an overview of existing research on analyzing desertification trends in Central Asia using MODIS data and the application of Google Earth Engine for analysis. Remote Sensing and Desertification Monitoring: Remote sensing techniques, particularly those utilizing satellite data, have been widely employed for monitoring desertification processes. The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor onboard various NASA satellites provides valuable data for assessing vegetation dynamics and land cover changes associated with desertification. Central Asia and Desertification: Central Asia, encompassing countries such as Kazakhstan, Uzbekistan, Turkmenistan, Kyrgyzstan, and Tajikistan, faces significant desertification challenges. Studies have highlighted the impacts of climate change, unsustainable land management practices, and population growth on desertification in the region. Monitoring and analyzing desertification trends in Central Asia are essential for developing targeted mitigation and adaptation strategies.

1 Introduction

Desertification studies in Central Asia: Several studies have focused on analyzing desertification trends in Central Asia using MODIS data and Google Earth Engine [1]. These studies have investigated vegetation dynamics, land cover changes, and the relationship between desertification and various environmental factors. They have provided valuable insights into the spatio-temporal patterns of desertification in the region and contributed to the understanding of its drivers [2].

Google Earth Engine for desertification analysis: Google Earth Engine is a cloud-based geospatial analysis platform that enables efficient processing of large-scale remote sensing datasets [3]. It offers a range of tools and algorithms for analyzing MODIS data and conducting land degradation assessments [4]. Researchers have utilized Google Earth Engine

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to analyze MODIS-derived indices, perform change detection, and investigate desertification trends in Central Asia [5].

2 Problem statement

The region of Central Asia, which is a part of Eurasia, has a very long history and was created as a distinctive natural territorial formation as a result of geological evolution. The natural geographic region of Central Asia is located in the center of the Eurasian continent, bounded by the Caspian Sea in the west, the Saur Mountains in the east, and the Hindikush, Safedkoh, Bandi-Turkistan, and Turkman-Khorasan regions in the north and south, respectively, at 53–54° north latitude. According to the geosystem principle, the western border's total length is 2,600 km (2,350 km), of which 900 km are the Caspian Sea's coasts. It should be noted, however, that the northwestern portion of the boundary was supposedly traversed by the Ural and Emba rivers in several textbooks and scientific publications. About Central Asia's northern boundary, there are three major perspectives. The first theory states that it is the meeting point of the Ob River and the Aral Basin of Kazakhstan's low mountains. The border runs through the northern foothills of Kazakhstan's low mountains, claims the third opinion [6].

Central Asia one of the biggest inland region in the world. It is situated in the desert of the subtropical area, in the desert, semi-desert, and steppe zones of the temperate region, in the latitude of the Mediterranean countries with a subtropical climate, in the center of the Eurasian continent. However, due to Central Asia's great distance from the ocean and open seas, its natural circumstances differ from those of the nations bordering the Mediterranean Sea. There are steep Himalayan-Paropomiz mountains between the warm Indian Ocean and the country, which prevent warm, humid air masses from reaching it. The distance to the nearest ocean, the Indian Ocean, is 1000 km. On the other hand, since the north of Central Asia lacks natural barriers like steep mountains, the dry and cold air masses from Siberia and the Arctic Ocean, which are far away, can easily arrive here. Although the Atlantic Ocean and the Mediterranean Sea are extremely far away, thanks to the western winds, they have a significant impact on the nature of our nation [7].

Fig. 1. Central Asia (Source:GRID-Arendal).

In the Central Asian region, despite its economic potential and importance for food security, there exist numerous environmental challenges. Among these, land degradation stands out as one of the most pressing issues, exerting a significant impact on the developmental prospects of all Central Asian countries [8].

The hydrographically isolated region in Central Asia, famously known for the Aral Sea, has been divided into three smaller water basins. This division has arisen due to the dwindling inflow from two major rivers, the Amudarya and the Syrdarya. Notably, one of these rivers, the Amudarya, has been the subject of purposeful restoration efforts, yielding some degree of success (as observed in the case of the Little Aral Sea [9]. However, the other two rivers remain interconnected, albeit with a continuous decline in the water table (Figure 1).

3 Materials and methods

3.1 Data

In order to monitor both natural and agricultural vegetation in the arid and semi-arid regions of Central Asia, a long-term dataset of differential and integral vegetation indices derived from NOAA and MODIS satellite data with relatively low spatial resolutions (1000 m and 250 m, respectively) during the growing season (April to September) was used [10]. The current condition and development of vegetated land surfaces can be evaluated using vegetation indices, such as the NDVI (Normalized Difference Vegetation Index) introduced by Rouse et al. in 1973 and the VCI (Vegetation state Index) proposed by Kogan in 1990. These indices are frequently aggregated over time to lessen the effect of cloud cover, for example by building 10-day maximum NDVI composites. As indicated by Spivak et al. in 2012, integrated vegetation indices (IVI) have been successful in assessing long-term changes in vegetation productivity. IVI calculates the total amount of green biomass present throughout the vegetation season by adding the NDVI composite values for each pixel [11]. To measure inter-seasonal fluctuations in the impact of meteorological conditions on vegetation status, the IVCI (Integral Vegetation Conditions indicator) is another indicator used. According to Kogan's work from 1990, values of VCI and IVCI below 30% serve as trustworthy markers of drought because they are associated with yield reductions of 20% or more [12].

3.2 MODIS imagine using desertification

The use of time series data from satellites offers an unmatched abundance of knowledge about how vegetation reacts to climatic changes. It requires a series of successive satellite measurements to effectively detect small changes in vegetation patterns over time. In this study, we evaluated the impact of sensor degradation on our capacity to identify trends [11,13,14]. We specifically concentrated on the study of data set 5, which was gathered from the MODIS sensors placed on the Terra and Aqua satellite platforms. Our investigation showed that the degradation of the blue band (at 3,470 nm) had the most significant impact on the simulated surface reflectance for the Terra MODIS sensor. Near-nadir viewing angles made this effect particularly noticeable. In the simulated aerosol conditions and across different surface types, a decrease in the normalized difference vegetation index (NDVI) in the range of 0.001 to 0.004 led to a fall of about -1. The patterns in the MODIS NDVI data across Central Asia that we saw matched the conclusions of our simulations. Notably, the negative NDVI trends between MODIS Terra (17.4%) and Aqua sensors differed by approximately three times [15-18].

The Moderate Resolution Imaging Spectroradiometer (MODIS) data collected by the NASA Terra and Aqua satellites, both of which have been in operation since 2002, provide a unique chance to evaluate the consistency of satellite-derived observations. These sensors use standardized algorithms to produce data products, and these MODIS standard products support a range of scientific applications. But recently, a number of studies have revealed contradictory results derived from the Terra and Aqua MODIS sensors. Estimates of ocean chlorophyll-a concentrations from 2010] and aerosols are included in these discrepancies. Such discrepancies may have major effects on how time series data are interpreted and may make it more difficult to spot time-dependent trends, particularly for MODIS products that rely on information from both Terra and Aqua MODIS sensors [19-22].

In this research, we studied at how sensor deterioration impacted trends in the Normalized Difference Vegetation Index (NDVI) as measured by MODIS over North American tundra and boreal forest regions. These biomes have been identified as having rapid productivity changes brought on by the climate. In order to implement these time-dependent patterns in sensor degradation, our method first calculated the degradation coefficients for each spectral band of MODIS before adding them into a condensed version of the MODIS atmospheric correction procedure. Then, focusing on Central Asia, we compared the predicted NDVI trends with the actual NDVI data trends collected from the Terra and Aqua MODIS sensors. The results we obtained imply that the degradation of the visible and near-infrared (NIR) bands on the Terra MODIS instrument is the only cause of the negative NDVI trends, which can be as low as -0.004 per year. This emphasizes how important it is to take sensor calibration concerns into consideration when evaluating trends in data spanning decades for variables related to the land, water, and atmosphere [7,22].

As satellite instruments develop and endure the harsh environment of space, sensor degradation is a common problem. In theory, onboard calibration processes can be used to correct sensor degradation. However, in practice, over the course of a mission's life, components like the solar diffuser, stimulation lights, and stability monitors that are necessary for onboard calibration also experience changes. Using "pseudo-invariant" desert objects to observe reflectance patterns is a useful alternative information source. These targets serve as a significant secondary reference for calibration because they appear to have maintained radiometric and spectral stability throughout the satellite era [23].

In order to evaluate the degradation of the Terra (2002-2020) and Aqua (2002-2022) MODIS sensors throughout the course of their operational lifetimes, we used top-of-atmosphere (TOA) reflectance data from MODIS C5 gathered over the Central Asian region. We obtained Level 1b TOA data for MODIS Bands 1 (red), 2 (NIR), and 3 (blue) from 16-day repeatable orbits over the target area to verify consistency in sensor viewing angles. We used bi-directional reflectance function (BRDF) coefficients that were site-specific and generated from the first three years of Terra and Aqua observations to normalize TOA reflectances [24]. We then used a second-order polynomial to fit the BRDF-normalized TOA data time series for each view angle (frame), spectral band, and mirror side. This made it easier to calculate sensor deterioration in proportion to the DSL (days since launch) number.

3.3 Google Earth Engine coding

In this research endeavor, we harness the formidable capabilities of Google Earth Engine (GEE) to undertake a comprehensive assessment of land degradation within a specific region, primarily relying on data derived from the Moderate Resolution Imaging Spectroradiometer (MODIS). The utilization of MODIS data is pivotal as it offers an extensive repository of valuable information encompassing vegetation indices, surface reflectance measurements, and land cover data. This wealth of data is strategically employed to detect, quantify, and scrutinize various aspects of land degradation phenomena. Through the amalgamation of

GEE's computational prowess, we endeavor to create a resilient and highly efficient analytical framework, a tool meticulously designed to facilitate the consistent monitoring of land degradation trends across time. Ultimately, this initiative is poised to enhance the quality of decision-making in the realm of land management by providing informed and data-driven insights [10, 25-27].

The MODIS sensor suite aboard NASA's Terra and Aqua satellites has proven indispensable in Earth observation, offering a treasure trove of remotely sensed data. The MODIS instrument captures a broad spectral range, providing information that is pivotal for assessing land degradation. Notably, this includes surface reflectance, which is essential for gauging changes in land cover, as well as vegetation indices like the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI), which serve as crucial indicators of vegetative health and stress.

Google Earth Engine emerges as a pivotal platform in this study, as it seamlessly integrates MODIS data and computational capabilities. GEE facilitates the efficient processing, analysis, and visualization of vast geospatial datasets, rendering it an indispensable asset for large-scale environmental monitoring. Through the exploitation of GEE's capabilities, we intend to construct a robust and versatile analytical tool capable of handling the complexities inherent in land degradation assessment.[28]

The core aim of this endeavor is the development of a cutting-edge land degradation monitoring framework. It will encompass the extraction and integration of MODIS data, the application of various analytical techniques, and the production of informative visualizations. This tool will empower researchers and land managers to delve into land degradation dynamics with precision, allowing for the identification of critical trends and hotspots.

By consistently monitoring land degradation trends, we aim to provide a valuable resource for land managers, policymakers, and researchers. Informed decisions regarding land use, conservation efforts, and mitigation strategies hinge on a thorough understanding of land degradation processes. Our research aims to bridge this knowledge gap, ultimately contributing to the formulation of effective, evidence-based land management policies and practices.

Data Acquisition and Preprocessing:

```
//Load MODIS MOD13Q1 Vegetation indices
//Load aoi: Area of Interest
//Filter date
var filtered=modis.filter(ee.Filter.date('2016-01-01','2021-12-31'))
print(filtered)
//Select Image
var modisNDVI=filtered.select('NDVI')
print(modisNDVI)
//Select an image and visualise
var image = ee.Image(modisNDVI.first())
var scaledImage = image.multiply(0.0001)
var visParams = {
  min:0,
  max:0.7,
  palette:['red','green']
}

Map.addLayer(scaledImage.clip(aoi),visParams,'NDVI')

//Map.addLayer(aoi)
//Scale the Collection and chart time series for a single point
var scaledNDVI = modisNDVI.map(function(image) {
  return image.multiply(0.0001)
  .copyProperties(image, ['system:time_start','system:time_end'])
});
```

```
var CAtest = ee.Feature(aoi4.first())
var chart=ui.Chart.image.series({
  imageCollection:scaledNDVI,
  region:CAtest.geometry(),
  reducer:ee.Reducer.mean(),
  scale:250}).setOptions({
    interpolateNulls:true,
    bestEffort:true,
    maxPexels:1e9,
    lineWidth:1,
    pointSize:3,
    title:'NDVI over time at Uzbekistan',
    vAxis:{title:'NDVI'},
    hAxis:{title:'Date',format:'YYYY-MMM',gridlines:{count:12}}
})
print(chart)
```

By combining the rich MODIS dataset and the computational power of Google Earth Engine, this study presents an efficient and scalable approach to monitor and analyze land degradation, providing valuable insights for sustainable land management and conservation efforts.

4 Results and discussion

According to their distinct properties, many surfaces display varying behaviors in terms of reflecting, transmitting, and absorbing radiation. The near-infrared (NIR) and red bands of remote sensing data differ from one another, and this difference is used by the Normalized Difference Vegetation Index (NDVI). These changes are brought on by unique characteristics of surfaces, such as the red-band absorption capabilities of chlorophyll pigments and the strong NIR-band reflectance of plant materials.

Simply put, NDVI is a statistic for determining how healthy and green a certain piece of vegetation is. NDVI values are often greater in healthy vegetation, which is characterized by an abundance of chlorophyll pigments. Little red light is reflected by lush, dense vegetation, but more red light is reflected by arid land and water. NDVI values for bare soil are typically calculated from the lowest NDVI values measured and are typically close to zero, whereas water surfaces produce negative NDVI values.

The values of the NDVI have a strong relationship with vegetation health, especially when it comes to the amount of water that is available in a specific area. In essence, higher NDVI values are anticipated in areas that have seen heavy rainfall, demonstrating a direct positive association. There is a statistically significant link between rainfall and NDVI, falling within the range of 0.15 to 0.53. This highlights how difficult it is to interpret trends in changes to vegetation cover using NDVI.

NDVI values for tropical and temperate forests, as well as for crops, typically vary from 0.15 to 0.53 when they are at the height of their growth. In the context of this study, data from the forest mask were used to limit the amount of crops in the chosen area. The distribution of NDVI values throughout the research region across different value classes is depicted graphically in Figure 2.

 https://doi.org/10.1051/e3sconf/202344306015

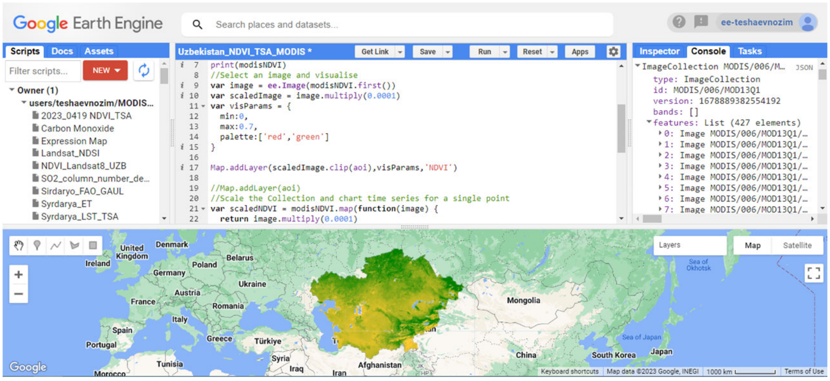

Fig. 2. Process vegetation index calculation using GGE.

Due to the prevailing arid climate in Central Asia, large expanses of land consistently exhibit NDVI values well below the annual average threshold of 0.2, as depicted in Figure 3. Approximately 68% of the total land area falls even further below this threshold, with values below 0.1. Conversely, less than 4% of the region, mainly situated within the northern mountainous terrain, displays annual NDVI averages exceeding 0.3. Consequently, even slight variations in annual NDVI readings can serve as indicators of potential environmental changes within the area. An initial assessment of presumed NDVI alterations can be made by roughly comparing the first half of the time-series (2002–2015) with the subsequent half (2015–2022). As illustrated in Figure 4, nearly the entire Central Asia region exhibits an augmentation in the annual mean NDVI, with an average increase of 0.02. Regions experiencing negative trends are scattered predominantly across western Central Asia and, to a lesser extent, in the far east; however, these decreases generally remain modest, seldom falling below -0.10.

Notably, the Aralkum desert in the western part of Central Asia demonstrates an average NDVI decline of approximately -0.10, with specific areas reaching as low as -0.15. To provide a more comprehensive understanding of the inter-annual dynamics of these changes, a detailed analysis is required.

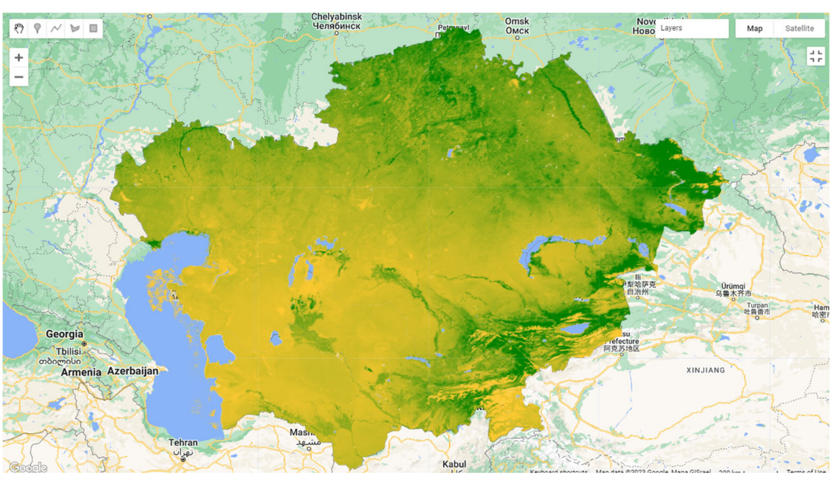

Fig. 3. Degradation and degraded areas in Central Asia.

In light of the arid environmental conditions and the geographical distribution of NDVI values across Central Asia, even minor shifts in these values can have significant implications. Therefore, conducting a comprehensive investigation into the factors driving these changes is of paramount importance. Further research should delve into the specific causes and consequences of these observed alterations, particularly in regions where negative trends are most pronounced. This will enable us to gain a deeper understanding of the environmental dynamics in Central Asia and their potential ramifications for the region's ecosystems and inhabitants.

The most pronounced association between precipitation and NDVI is evident in Steppe regions, with Desert and Desert steppe areas following in terms of the strength of this relationship. In contrast, desert areas do indicate some level of correlation, but the magnitudes of these correlations are generally too insignificant. They often fall within the margin of error inherent in the NDVI and precipitation datasets, thus failing to demonstrate a robust connection. Desert Vegetation displays a notably feeble NDVI response to increases in precipitation, while Subtropical and desert regions appear to be largely unaffected by direct influences from precipitation. However, Subtropical and desert regions, with particular emphasis on the Subtropical, exhibit an increase in NDVI as temperatures rise. A similar trend is observed in desert Steppe areas. In the case of Desert regions, a connection exists as well, but it is inversely related, meaning that higher temperatures in these areas result in a decrease in NDVI. It is important to acknowledge, however, that there is a significant degree of noise in the data, and while these relationships are present, they remain relatively weak. In Steppe regions, there is a notably robust correlation between precipitation and NDVI, with Desert and Desert Steppe areas exhibiting a slightly weaker but still discernible relationship. Desert regions also display some correlation, albeit with values that are generally too small to be considered statistically significant when accounting for the inherent error margins within the NDVI and precipitation datasets. Conversely, Desert Vegetation exhibits a limited NDVI response to increases in precipitation, while Subtropical and desert regions appear to be largely unaffected by direct influences from precipitation. However, Subtropical and desert regions, particularly the Subtropical zone, demonstrate an increase in NDVI as temperatures rise. This trend is similarly observed in desert Steppe areas. In the case of Desert regions, a connection exists as well, albeit with an inverse relationship, where higher temperatures correspond to a reduction in NDVI. It is essential to recognize that the data contains a considerable amount of noise, and while these connections are present, they remain relatively weak.

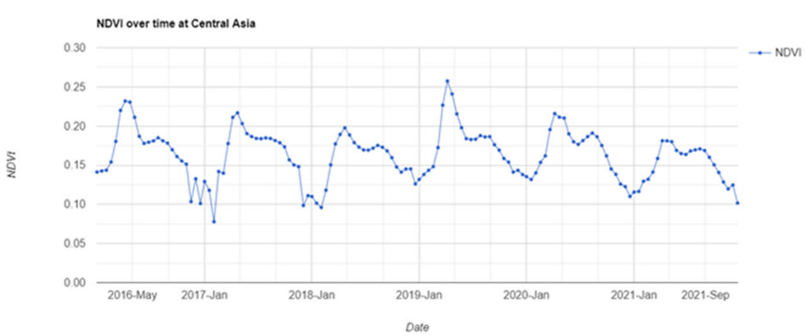

Fig. 4. Dynamics of degraded areas in Central Asia 2016-2021.

In summary, the strength of the relationship between precipitation and NDVI varies across different ecological regions, with Steppe areas exhibiting the strongest correlation, followed by Desert and DesertSteppe regions. Desert regions also show some correlation, but it is generally too weak to be considered statistically significant. Meanwhile, Subtropical and desert regions seem to be less influenced by precipitation but exhibit an increase in NDVI with rising temperatures. Desert Steppe areas follow a similar temperature-related trend, while Desert regions show an inverse relationship between temperature and NDVI. However, it is important to note that these relationships, while present, are characterized by a notable degree of variability and uncertainty.

Between 2015 and 2021, Central Asia as a whole did not exhibit any significant trends in annual temperature or precipitation, as illustrated in the bottom-right panel of Figure 4. However, specific subregions within Mongolia did experience noteworthy trends. The general annual mean temperature trend displayed a negative trajectory, indicating a slight cooling effect. This cooling trend was observed in isolated clusters across Central Asia, with an average annual decline of 0.08 K. In terms of precipitation trends, a distinct pattern emerged in a contiguous southwest corridor at the heart of Central Asia, with two smaller areas of interest in the west and far east. Notably, only the northernmost region demonstrated an increase in precipitation, while the larger surrounding areas experienced a decrease. Further analysis of the annual sequences of temperature, precipitation, and NDVI at five selected locations, as well as the Central Asian average, revealed that none of the five chosen points exhibited a significant trend in temperatures. However, sites situated to the east and west demonstrated a statistically significant decline in precipitation at a significance level of $\alpha = 0.05$, with site A only narrowly missing statistical significance. It is worth noting that the decline in precipitation was more pronounced in the central Aralkum area. At locations A and B, albeit relatively weak, a correlation was observed between NDVI and precipitation ($r^2 = 0.15$ and $r^2 = 0.27$, respectively). However, particularly at location A, it appears unlikely that precipitation is the predominant driver of NDVI. This assertion is based on the considerably steeper decline in NDVI, which even appears contradictory from 2015 to 2021. During this period, precipitation exhibited a slight increase, yet NDVI values sharply declined from 0.15 to 0.29. This shift represents the most substantial difference between any two years at the selected locations. Meanwhile, at location B, the downward trend in NDVI was more moderate and not readily explained by changes in temperature or precipitation. For instance, in years characterized by local precipitation minima (e.g., 2015 or 2021), NDVI actually exhibited an upward trajectory. These results provide an overview of the interrelationships between climatic variables and NDVI values during the years 2015 to 2021 within various vegetation zones.

Table 1. Correlation between NDVI and temperature and between NDVI and precipitation for the time-series.

	NDVI ↔ Temp. correlation		**NDVI ↔ Precip. correlation**		**NDVI ↔ Temp. *shifted* correlation**		**NDVI ↔ Precip. *shifted* correlation**		***Temperature trend***		***Precipitation trend***	
areas	r-value	r^2	r-value	r^2	r-value	r^2	r-value	r^2	MKp	r-value	MKp	r-value
South	0.25	0.23	0.28	0.27	0.22	0.05	0.49	0.24	0.22	0.07	0.09	-0.32
west	-0.02	0	0.48	0.23	-0.01	0	0.46	0.21	0.25	0.04	0.01	-0.37
north	-0.12	0.02	-0.4	0.16	-0.23	0.11	-0.24	0.41	0.55	0.02	0.02	-0.39
east	-0.27	0.07	0.03	0	-0.44	0.19	0.33	0.11	0.49	0.04	0.62	-0.16
center	0.08	0.01	-0.04	0	0.02	0	0.17	0.03	0.37	0.01	0.77	-0.14

5 Conclusion

Long-term NDVI (Normalized Difference Vegetation Index) trends in Central Asia have historically been classified as negative. These trends have been examined using AVHRR data since the early 2000s and MODIS data from 2015 onward. Our most recent analysis, however, refutes this widely held belief. In significant areas surrounding the Aralkum, we have observed encouraging trends that we attribute to changes in human land use patterns in these desert-covered regions. We have also located the only major NDVI reductions in Central Asia close to these regions. These decreases are a result of the semi-arid being temporarily reduced by fire occurrences.

Additionally, we have noticed a significant rise in NDVI in eastern Mongolia, which we ascribe to July's increasing precipitation and cooling temperatures, which resulted in more water being available and higher NDVI values. Additionally, although the linkage in this area is somewhat less, smaller-scale NDVI rises on the eastern slopes of Uzbekistan have been linked to dropping July temperatures.

We have also found minor NDVI increases in other regions of Central Asia in addition to these major changes. These increases, however, lack statistical significance and must be viewed as speculative. We partially blame this limitation on the difficulties that trend investigations entail, particularly given the length of our datasets. When we examine data from the most current SPOT sensor or when various indices are taken into consideration, many additional trend sites become inconclusive, however the key patterns we have described above continue across nearly all tested scenarios.

In general, our results cast doubt on the dominantly negative NDVI trends in Central Asia, indicating noteworthy positive developments in particular locales, and underscoring the significance of taking into account different elements and data sources in trend analysis.

Significant research gaps regarding the evaluation of landscape dynamics in the region are highlighted by the Central Asia case study. An innovative methodology that combines breakpoint analysis (identifying tipping points), categorization of ecosystem reactions, and conventional trend analysis is urgently needed for assessing ecosystem conditions. It is crucial to establish a GIS-based mapping and assessment tool that can identify crucial turning points throughout Eurasia and is geared for large-scale ecosystem functioning assessments. Studying the regional heterogeneity in both the type and timing of trend shifts as well as the direction of change is particularly relevant in ecosystem assessment research, in addition to identifying the timing, occurrence, and form of abrupt shifts. It is crucial to maintain long-term, high-quality, continuous, and harmonized Earth Observation time series, covering both climate and vegetation information, in order to produce reliable assessments of environmental changes and land dynamics. Scale implications, including spatial resolution and observation length, are another crucial area that needs more study. In the framework of the Central Asia case study, it is examined what scale can be used to generate trustworthy indicators of ecosystem functioning.

Further, accurate driver attribution continues to be difficult, especially in light of the co-occurrence of global and local drivers. Additional information on the drivers and specialized skills are required to address this difficulty. The two case studies also show that land-use change modeling is an area of research that is constantly evolving.

- The modeling of land-use change factors.
- Simulating the scale dependency of land-use change drivers.
- -Progress in predicting where and how much land will change its usage.
- -Adding ecological feedback to models of land-use change.

Research on landscape dynamics is primarily driven by the need to understand how human activity affects landscapes and how this understanding might guide future land planning and ecosystem management in Central Asia's dry lands. Assessing anthropogenic changes in disturbance regimes that have altered landscape patterns and dynamics has received a lot of attention. For instance, variations in fire disturbance patterns brought on by climatic changes or fire suppression techniques, as well as the effects of land use and forest management practices like logging, have been the focus of research.

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